

SECP3133-02 High Performance Data Processing

# **Project 1 Final Report**

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### FACULTY OF COMPUTING

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## 1.0 Introduction

### 1.1 Project Background

As technology of modern days grows, speed and effectiveness of computer processes has become significant to those who require data to work, which practically includes almost every existing field in the market. High performance data processing, being one of the more recent technology innovations meant to accelerate compute rate, has become an important topic in data analytics. Hence, from this project, we would like to evaluate the practicality of said innovation:

- 1. Are high performance computing (HPC) solutions truly accelerating the computing processes, specifically the data cleaning process?
- 2. How does each python library (Modin, Dask, Joblib etc) differ in the ways they handle HPC?
- 3. Which library delivers the best performance when dealing with 100k+ datasets?

Through this project, we want to make a conclusion from the listed questions above, and potentially help answer questions by more IT users or business users, whom may be interested in discovering pros and cons of each optimization library.

### 1.2 Objectives

- To develop a web scraping system using several libraries, such as BeautifulSoup, Selenium and more to extract up to 100,000 real estate data from the <u>iProperty Malaysia website</u>.
- To perform heavy loaded data cleaning on said dataset.
- To utilize four libraries with optimization techniques including multithreading, multiprocessing, Spark, etc. to enhance data processing efficiency
- To evaluate and compare performance before and after optimization based on:
  - o Time
  - o Memory usage
  - o CPU usage
  - o Throughput
- To visualize insights and performance metrics using chart and graphs for clear comparison

## 1.3 Target Website & Data to be Extracted

The target website for data scraping in this project is <u>iProperty Malaysia</u>, a well-known online real estate platform that provides listings for various residential properties that are available for sale across Malaysia. The site offers detailed information on each property,

including its location, price, size, furnishing status, type and the contact agent responsible for the listing.

The data extracted from iProperty includes the following key attributes:

- 1. Property title (e.g., apartment, condominium, terrace house)
- 2. Location (state and city)
- 3. Price
- 4. Built-up size (in square feet)
- 5. Furnishing status (furnished, partially furnished or unfurnished)
- 6. Agent name

This information allows for valuable insights into the Malaysian property market and also provides a robust dataset to evaluate the performance of different high-performance data processing techniques in later stages of the project.

Note: There exist 3 different card styles for properties based on time of publish

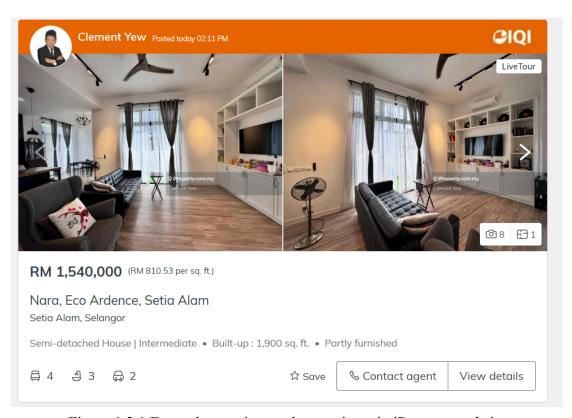


Figure 1.3.1 Example premium style containers in iProperty website

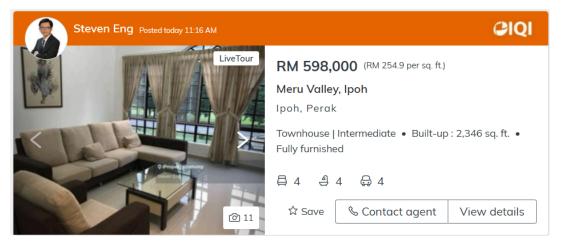


Figure 1.3.2 Example featured style containers in iProperty website



Figure 1.3.3 Example basic style containers in iProperty website

# 2.0 System Design and Architecture

## 2.1 Architecture

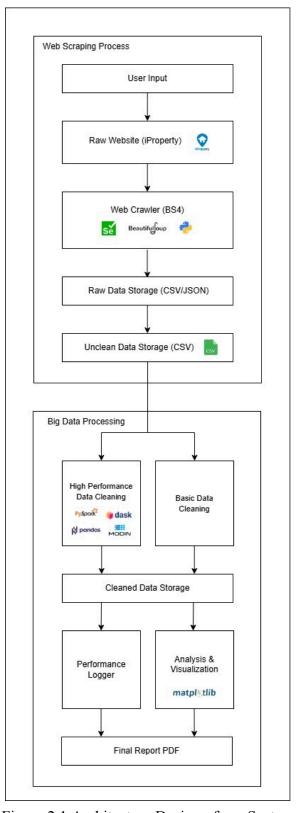


Figure 2.1 Architecture Design of our System

## 2.2 Tools and Framework used

Category	Software/Application/Library/Website
Documentation	Google Doc
Progression Monitoring	Github
Architecture Design	Draw.io
Web Scraping Library	BeautifulSoup, Selenium
Initial Dataset Form	Excel file (.csv)
IDE	Google Colab
Coding Language	Python
Data Visualization	Matplotlib Library (Python)
Basic Data Cleaning	Pandas Library (Python)
Optimization Libraries	Modin & Ray, Polars, Spark, Joblib, Multiprocessing
Database Management System	SQLite

Table 2.2 Tools used in this Project

## 2.3 Roles of team members

Member	Role	Responsibility
Lim Jing Yong	Lead Crawler Developer	<ul> <li>Leading the implementation of the web crawler using BeautifulSoup and Selenium</li> <li>Handle pagination, data structure identification, and crawl delay management</li> <li>Ensure ethical scraping practices and data completeness</li> <li>Optimization library used: Modin &amp; Ray</li> </ul>
Lee Soon Der	Data Cleaning and Storage Specialist	<ul> <li>Leading the cleaning and preprocessing of the raw data</li> <li>Standardize fields and manage datasets for further processing</li> <li>Optimization library used: Polars</li> </ul>
Jaslene Yu	Performance and Optimization Lead	<ul> <li>Leading the process applying high performance computing techniques</li> <li>Monitor and document CPU/memory usage and system throughput</li> <li>Optimization library used: Multiprocessing &amp; Spark</li> </ul>
Nik Zulaikhaa	Performance Analyst and Documentation Lead	<ul> <li>Leading the comparison of optimization result</li> <li>Generate visualizations and compile the final technical report</li> <li>Optimization library used: Joblib</li> </ul>

Table 2.3 Member Roles

## 3.0 Data Collection

## 3.1 Crawling method

To collect the required property data from iProperty Malaysia, we implemented a **web crawling system** by using **Python** by combining the **Selenium** library with **BeautifulSoup** for HTML parsing. Selenium was used to simulate a real browser environment that handles dynamic content loading. BeautifulSoup was implemented to extract and parse the HTML structure of the web pages.

The crawling process follows a **dynamic web scraping approach**, as the targeted website, the iProperty requires JavaScript execution to fully render the property listings. We automated **Chromium** using a **headless** mode setup, enhanced with **fake user agents** to mimic real browsing behavior and avoid bot detection.

During the crawling process, **CSS selectors** with partial class matching were used to accurately scrape the property title, price, location, details, and agent name. The data was collected from **multiple pages** across **different areas**, and the final output was compiled into a CSV file.

### 3.2 Number of records collected

A total of 160,000+ records of properties are recorded.

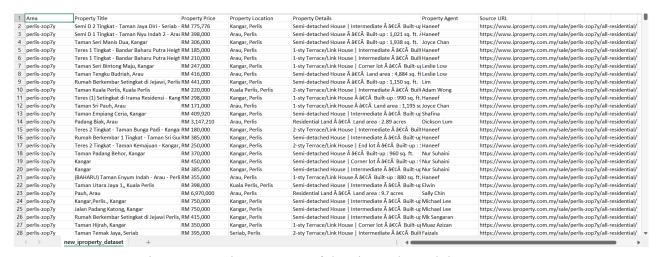


Figure 3.2.1 First 27 rows of data in uncleaned dataset

3512 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 6,546,428	Simpang Ampat, Penang	Residential Land  • Land area: 96,271 sq. ft. 0	Crystal Tee	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3513 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 9,980,292	Simpang Ampat, Penang	Residential Land  â€C Land area: 146,769 sq. ft. 0	rystal Tee	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3514 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 9,149,536	Simpang Ampat, Penang	Residential Land  â€C Land area: 134,552 sq. ft. 0	rystal Tee	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3515 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 12,579,252	Simpang Ampat, Penang	Residential Land  â€C Land area: 184,989 sq. ft. 0	rystal Tee	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3516 simpang-ampat-41r Royale Infinity, Simpang Ampat	RM 380,000	Simpang Ampat, Penang	Condominium  â€C Built-up: 1,480 sq. ft. J	ass Kong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3517 simpang-ampat-41r Simpang Ampat	RM 570,000	Simpang Ampat, Penang	Semi-detached House  â€C Built-up: 1,585 sq. ft. J	etson Yip	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3518 simpang-ampat-41r Hijauan Hill, Simpang Ampat	RM 650,000	Simpang Ampat, Penang	Semi-detached House  â€C Built-up: 2,280 sq. ft. i.A	Inders Ong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3519 simpang-ampat-41; Batu Kawan, Simpang Ampat	RM 858,000	Simpang Ampat, Penang	2-sty Terrace/Link House  â€C Built-up : 2,290 sq. (	hris Huah	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3520 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 261,000	Simpang Ampat, Penang	1-sty Terrace/Link House  â€C Land area: 1,195 sck	loay CK	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3521 simpang-ampat-41; Taman Lembah Indah, Simpang Ampat	RM 1,400,000	Simpang Ampat, Penang	Bungalow  • Built-up : 4,500 sq. ft.	teven Hng	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3522 simpang-ampat-41; Royale Infinity, Simpang Ampat	RM 680,000	Simpang Ampat, Penang	Condominium   Intermediate  • Built-up : 1,400 k	Celly Yee	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3523 simpang-ampat-41; Taman Lembah Indah, Simpang Ampat	RM 660,000	Simpang Ampat, Penang	3-sty Terrace/Link House  • Built-up : 2,524 sq. V	Vinson Chong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3524 simpang-ampat-41; Taman residensi alma, Simpang Ampat	RM 700,000	Simpang Ampat, Penang	2-sty Terrace/Link House  • Built-up : 1,640 sq. S	uzzane Lee	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3525 simpang-ampat-41; Taman Idaman, Simpang Ampat	RM 810,000	Simpang Ampat, Penang	2-sty Terrace/Link House   Corner lot  • Built-uj C	H Ong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3526 simpang-ampat-41; Taman Perwira Indah, Simpang Ampat	RM 430,000	Simpang Ampat, Penang	2-sty Terrace/Link House  â€C Built-up : 2,000 sq. F	ionne Seah	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3527 simpang-ampat-41; Taman Perwira, Simpang Ampat	RM 315,000		1-sty Terrace/Link House  â€C Built-up : 1,200 sq. L		https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3528 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 550,000	Simpang Ampat, Penang	2-sty Terrace/Link House   Intermediate  • Built A	llex Ho	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3529 simpang-ampat-41; Taman Lembah Indah, Simpang Ampat	RM 866,000	Simpang Ampat, Penang	3-sty Terrace/Link House   Corner lot  â€C Built-u  C	H Ong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/al
3530 simpang-ampat-41; Raintree Park, Simpang Ampat	RM 480,000		2-sty Terrace/Link House   Intermediate  • Built F		https://www.iproperty.com.my/sale/simpang-ampat-41pqd/al
3531 simpang-ampat-41; Taman Tambun Emas, Simpang Ampat	RM 699,000	Simpang Ampat, Penang	3-sty Terrace/Link House   Corner lot  â€C Built-uj N	licol Tan	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3532 simpang-ampat-41r Taman Murai Jaya, Simpang Ampat	RM 680,000	Simpang Ampat, Penang	Semi-detached House   Intermediate  • Built-ur C	H Ong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3533 simpang-ampat-41r Bandar Tasek Mutiara, Simpang Ampat	RM 950,000	Simpang Ampat, Penang	Semi-detached House   Corner lot  • Built-up : 20	H Ong	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/al
3534 simpang-ampat-41r Taman Lembah Indah, Simpang Ampat	RM 608,000	Simpang Ampat, Penang	2-sty Terrace/Link House   Intermediate  • Built J	etson Yip	https://www.iproperty.com.my/sale/simpang-ampat-41pgd/al
3535 simpang-ampat-41r Taman Eco Meadow, Simpang Ampat	RM 850,000	Simpang Ampat, Penang	2-sty Terrace/Link House   Intermediate  8€¢Â Built J	ass Ooi	https://www.iproperty.com.my/sale/simpang-ampat-41pgd/al
3536 simpang-ampat-41; Taman Tambun Indah, Simpang Ampat	RM 1,600,000	Simpang Ampat, Penang	Bungalow   Intermediate  • Built-up : 3,016 sq. F	rancis Neow	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/al
3537 simpang-ampat-41; Bandar Tasek Mutiara, Simpang Ampat	RM 690,000		Semi-detached House   Intermediate  • Built-ur		https://www.iproperty.com.my/sale/simpang-ampat-41pqd/all
3538 simpang-ampat-41; Eco Bloom, Simpang Ampat	RM 470,000	Simpang Ampat, Penang	Condominium   Intermediate  • Built-up : 901 s A	andy Chuah	https://www.iproperty.com.my/sale/simpang-ampat-41pqd/al
3539					
> new iproperty dataset +					

Figure 3.2.2 Last 27 rows of data in uncleaned dataset (until 163538th row)

The dataset has the following fields as below:

- 1. Area The state or city where the property is located.
- 2. Property Title The title or headline of the property listing.
- 3. Property Price The listed selling price of the property.
- 4. Property Location A more specific address of the property.
- 5. Property Details Detailed information about the property include size, type and furnishing.
- 6. Property Agent The name of the real estate agent or agency responsible for selling or listing the property.
- 7. Source URL The website link to the original source page.

### 3.3 Ethical considerations

To ensure ethical web scraping, we followed these key practices:

- Polite Crawling: Crawl delays and request throttling were applied to avoid overloading the server.
- No Sensitive Data: Only publicly available property listing information was collected. No personal or confidential data was accessed.
- Academic Use Only: All data is used strictly for educational purposes within the course scope and will not be used commercially.
- Secure Data Handling: The dataset is securely stored and not publicly shared.

## 4.0 Data Processing

## 4.1 Cleaning methods

Several cleaning methods are utilized to transition our newly built dataset of 160k+ data into a more readable format to help ease the process of analysis. More details regarding data cleaning can be referred to in section 4.3.

Method	Involved Field	Description
Data Splitting	Property Title	By comma
	Property Location	By comma
	Property Detail	By separator
Title Casing	Property Title	First character uppercase
	Property Agent	First character uppercase
Punctuation Removal	Property Price	"RM", comma
Data Type Conversion	Property Price	string to int
Special character replacement	Property Details	Multiple characters to " "
Numeric Value Extraction	Property Details	Extract property size
Filling Missing Values	Property Details	As "None"
Row Filtering	Property Agent	Remove non-agent name data
Null Data Removal	Entire Dataset	Remove data based on condition

Table 4.1 Data Cleaning Methods and related Fields

### 4.2 Data Structure

The cleaned property dataset was stored in an **SQLite database** for efficient data management.

A copy of the original DataFrame was created to preserve the raw data. The cleaned data was then saved into the SQLite database using the **to\_sql()** method, where it was stored in a table named **cleaned\_data**. If the table already existed, it was replaced with the new data.

The database file (**iproperty.db**) was then exported and made available for download in Google Drive. This allows easy access to the cleaned data for further analysis in SQLite-compatible applications.



Figure 4.2.1 Database Structure in SQLite

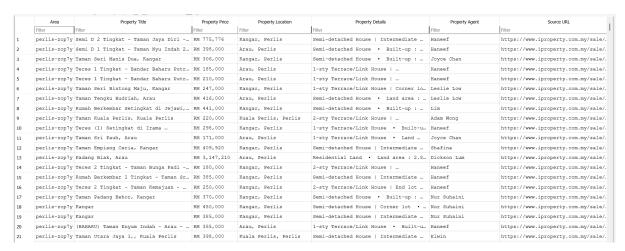


Figure 4.2.2 Raw data table in SQLite

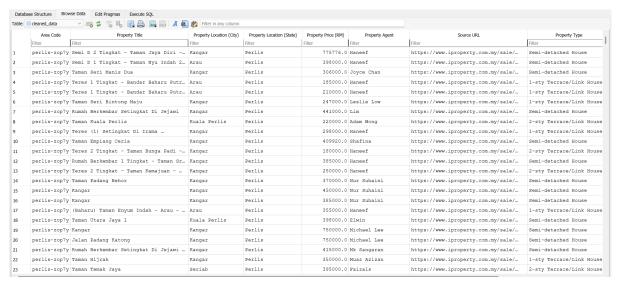


Figure 4.2.3 Cleaned data table in SQLite

### 4.3 Transformation and formatting

Reformatting Property Titles:

```
df['Property Title'] = df['Property Title'].str.split(',').str[0]
df['Property Title'] = df['Property Title'].str.title()
```

- Capitalized the first letter of each word.
- Separated titles by commas for improved readability.

### **Dividing Property Locations:**

```
split_cols = df['Property Location'].str.split(', ', expand=True)
split_cols.columns = ['Property Location (City)', 'Property Location (State)']
df.drop(columns=['Property Location'], inplace=True)
df.insert(2, 'Property Location (City)', split_cols['Property Location (City)'])
df.insert(3, 'Property Location (State)', split_cols['Property Location (State)'])
```

• Split into two components: city and state.

#### Handling Property Prices:

```
df['Property Price'] = df['Property Price'].str.replace('RM', '', regex=False)
df['Property Price'] = df['Property Price'].str.replace(',', '', regex=False)
df['Property Price'] = pd.to_numeric(df['Property Price'], errors='coerce')
df.rename(columns={'Property Price': 'Property Price (RM)'}, inplace=True)
```

- Removed entries with NaN values to ensure data integrity.
- Converted prices from string format to integers.
- Renamed the column to "rm" and separated data by commas.

#### Standardizing Property Agent Names:

```
df['Property Agent'] = df['Property Agent'].str.title()
df['Property Agent'] = df['Property Agent'].apply(
    lambda x: None if re.search(r'\bsdn\.?\s*bhd\.?\b', str(x), re.IGNORECASE) else x
)
```

- Capitalized the first letter of each agent's name.
- Filtered out non-agent names (e.g., company names).

#### Splitting Property Details:

```
def parse_property_details(detail):
    if pd.isnull(detail):
       return pd.Series([None, None, None])
   clean_detail = re.sub(r'[^\x00-\x7F]+', ' ', str(detail))
   type_match = re.search(r"^(.*?)Built-up", clean_detail, re.IGNORECASE)
    if type_match:
       raw_type = type_match.group(1).strip()
       property_type = re.split(r'\s*\|\s*', raw_type)[0]
       property_type = None
   area\_match = re.search (r'Built[-\s]*up[^0-9]*([\d,]+)\s*sq\.?\s*ft', clean\_detail, re.IGNORECASE)
   area = area_match.group(1).replace(',', '') if area_match else None
   # extract Furnishing status
   furnishing = "Unknown
   if re.search(r'\bUnfurnished\b', clean_detail, re.IGNORECASE):
       furnishing = 'Unfurnished'
   elif re.search(r'\bPartially Furnished\b', clean_detail, re.IGNORECASE):
       furnishing = 'Partially Furnished'
   elif re.search(r'\bFully Furnished\b', clean_detail, re.IGNORECASE):
       furnishing = 'Fully Furnished'
   elif re.search(r'\bFurnished\b', clean_detail, re.IGNORECASE):
       furnishing = 'Furnished'
   return pd.Series([
       property_type.strip() if property_type else None,
       float(area) if area else None,
       furnishing
```

- Divided into three categories: type, size (in sqft), and furnishing status using the separator "|".
- Converted size from string to float for quantitative analysis.
- Removed entries with sizes below 70 sqft to eliminate illogical data.
- Replaced NaN values in furnishing status with "Unknown."

# **5.0 Optimization Techniques**

## 5.1 Methods used

Person In Charge	Library
Lee Soon Der	Polars: A high performance DataFrame library designed for faster data processing, especially for large volumes of dataset. It is built with rust as its core, offers multi-threaded executions and supports lazy evaluation, making it more memory-efficient than pandas.
Lim Jing Yong	Modin & Ray: Modin is a high-performance drop-in replacement for pandas that speeds up data processing by automatically distributing operations across all CPU cores. Ray, which is a general purpose distributed execution engine, is used by Modin to perform the parallel operation efficiently.
Jaslene Yu	Multiprocessing: A library in Python allows a program to utilize multiple CPU cores simultaneously, enabling parallel execution of tasks. This is particularly useful for CPU-bound data processing operations where processing can be split across processes to reduce runtime.
	Spark: Apache Spark is a distributed computing framework designed for large-scale data processing across clusters. It optimizes performance using in-memory computation, lazy evaluation, and task parallelism. Spark's DataFrame and SQL APIs allow developers to express complex data workflows that Spark automatically optimizes under the hood using the Catalyst optimizer and Tungsten engine.
Nik Zulaikhaa	Joblib: Joblib is a parallel processing library in Python that simplifies running tasks concurrently using multiple CPU cores. It is ideal for speeding up repetitive, CPU-bound operations like data parsing by distributing workloads efficiently with minimal code changes.

## 5.2 Code Overview

Person In Charge	Code
Lee Soon Der	Use CLI command to download Polars  [ ] pip install polars
	Load csv in lazy mode  df_lazy = pl.read_csv("new_iproperty_dataset.csv").lazy()
	Execute lazy plan to collect all previous cleaning processes and execute everything in parallel df = df_lazy.collect()
Lim Jing Yong	Use CLI command to download Modin with Ray  !pip install -U modin[ray] ray
	Implement Modin into Pandas import pandas as pd to import modin.pandas as pd
	<pre>Import Ray library, initiate the engine and set it to the OS's environment for Modin to use it import ray  ray.init(ignore_reinit_error=True) os.environ["MODIN_ENGINE"] = "ray"</pre>
	Confirming which engine Modin is using (another option is Dask)  import modin.config as modin_cfg print(modin_cfg.Engine.get())  Ray
Jaslene Yu	Multiprocessing Import Multiprocessing library import multiprocessing as mp

mp.Pool.map() divides the tasks into smaller chunks in order to processes them in parallel using all available CPU cores mp.cpu count() def parallel\_parse(series, func, processes=None): with mp.Pool(processes or mp.cpu\_count()) as pool: results = pool.map(func, series) results = pool.map(runc, serses, return pd.DataFrame(results, columns=[]'Property Type', 'Property Size (sqft)', | Property Furnishing Status']) To avoid the infinite loop of processes by ensuring that the multiprocessing pool is only created when the script is executed directly == " name main **Spark** Import SparkSession class from PySpark's sql module from pyspark.sql import SparkSession Using Spark SQL API for further operation spark = SparkSession.builder \ .appName("iProperty Data Cleaning") .getOrCreate() UDF is applied to the DataFrame in parallel across the partitions of the data and PySpark will distribute the UDF tasks across worker nodes df = df.withColumn("parsed", parse udf(col("Property Nik Zulaikhaa Use CLI command to download JobLib !pip install joblib Imported Parallel and delayed from JobLib from joblib import Parallel, delayed Joblib is used to parallelize parsing tasks across CPU

cores

## **6.0 Performance Evaluation**

## 6.1 Before optimization

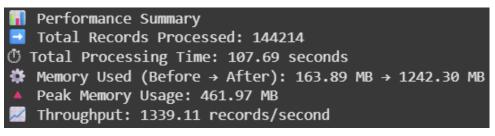
Below shows several screenshots of the basic data cleaning process's performance without optimization techniques. Session is restarted after every run to ensure memory usage is started from the initial state.

#### Run 1:

```
Performance Summary
Total Records Processed: 144214

Total Processing Time: 113.38 seconds
Memory Used (Before → After): 163.79 MB → 1241.14 MB
Peak Memory Usage: 456.80 MB
Throughput: 1271.91 records/second
```

### Run 2:



#### Run 3:



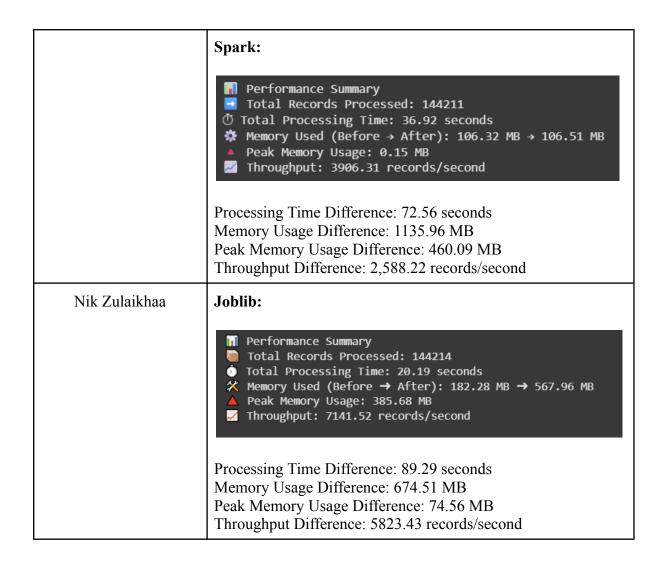
#### From the three runs:

Average Processing Time	109.48 seconds
Average Memory Used	1242.47 MB
Average Peak Memory Usage	460.24 MB
Average Throughput	1318.09 records/second

Table 6.1 Average Performance of 3 runs of unoptimized data cleaning

# 6.2 Comparison to Optimized Solution

Person In Charge	Performance
Lee Soon Der	© Elapsed Time: 5.15 sec  III Memory Used (Start → End): 575.35 MB → 746.41 MB  Ø Peak Memory (tracemalloc): 99.14 MB  Inroughput: 27,990.23 records/sec  Total Records Cleaned: 144214
	Processing Time Difference: 104.33 seconds Memory Usage Difference: 496.06 MB Peak Memory Usage Difference: 361.1 MB Throughput Difference: 26672.14 records/second
Lim Jing Yong	Modin & Ray
	Performance Summary Total Records Processed: 144214  Total Processing Time: 26.41 seconds Memory Used (Before → After): 223.07 MB → 393.36 MB Peak Memory Usage: 71.74 MB Throughput: 5460.38 records/second
	Processing Time Difference: 83.07 seconds Memory Usage Difference: 849.11 MB Peak Memory Usage Difference: 388.5 MB Throughput Difference: 4142.29 records/second
Jaslene Yu	Multiprocessing
	Performance Summary Total Records Processed: 144214  Total Processing Time: 19.57 seconds Memory Used (Before → After): 164.45 MB → 456.23 MB Peak Memory Usage: 107.99 MB Throughput: 7368.01 records/second
	Processing Time Difference: 89.91 seconds Memory Usage Difference: 786.24 MB Peak Memory Usage Difference: 352.25 MB Throughput Difference: 6049.92 records/second



## 6.3 Graph Visualization

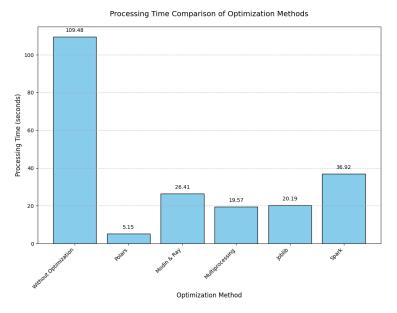


Figure 6.3.1 Graph of Comparison between Libraries (Processing Time)

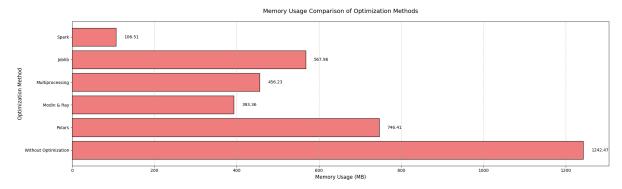


Figure 6.3.2 Graph of Comparison between Libraries (Memory Usage)

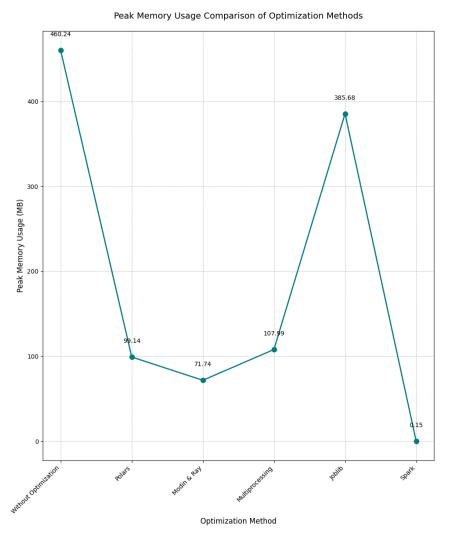


Figure 6.3.3 Graph of Comparison between Libraries (Peak Memory Usage)

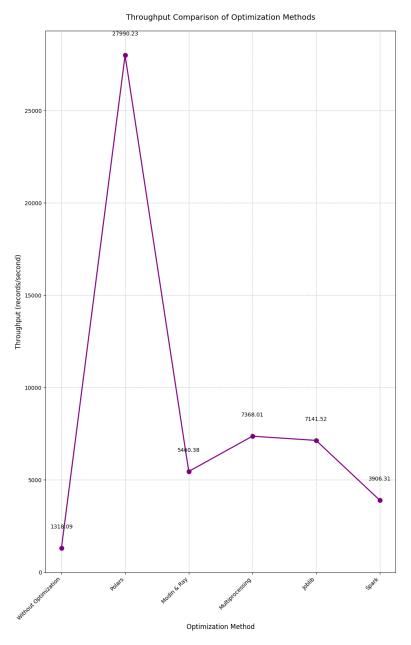


Figure 6.3.3 Graph of Comparison between Libraries (Throughput)

## 7.0 Challenges & Limitations

## 7.1 Challenges

- Iproperty website provides **multiple wrapper styles** (see <u>section 1.3</u>) which was unexpected initially. Due to BeautifulSoup's method of extracting data, additional modification must be done to our data scraping coding to scrap all wanted data.
- Iproperty website only has a maximum of 100 pages per filter, hence **area codes** must be listed individually in order to iterate between areas to scrap more than 100k data.
- During the data scraping process, Iproperty website's **CAPTCHA system** prevented us from extracting data. This issue was solved through usage of a user agent and an inconsistent (randomly timed) WebDriverWait() function.
- The property data in Iproperty website has **multiple blank columns and incorrect measurements** (exp. Property Size 1 sqft, NULL data for Property Furnishing Status, weird symbols in Property Name). This issue is addressed through criteria-based row dropping.
- Implementing Apache Spark for optimization required translating the existing data cleaning logic into Spark's **specific terminology and syntax**. For instance, operations like filtering and column manipulation, while conceptually similar to Pandas, necessitate the use of Spark's DataFrame API and functions (e.g., filter(), withColumn()), leading to a significant rewrite of the cleaning code.

### 7.2 Limitations

- An attempt was made to use Modin + Dask library for advanced optimization, however due to usage of **apply() function** in our data cleaning method, coding becomes too complicated and requires big modifications.
- Some high-performance libraries are **designed for processing massive volumes** of datasets with millions of rows such as Dask, Vaex and Apache Flink. When applied to smaller datasets like ours (~160k rows), the optimization performance will be lower than the lightweights tools like Pandas due to unnecessary overhead which results in slower execution and reduced efficiency.
- Although Joblib enabled parallel cleaning of the "Property Details" column, the task was lightweight, and multiprocessing overhead outweighed the benefits for small datasets (~240 rows), resulting in minimal performance gains.

-	A key inconsistency with the Apache Spark implementation was a lower final row count compared to other methods, even with identical cleaning logic, likely due to differences in regex handling.

## 8.0 Conclusion

## 8.1 Our Findings

Throughout this project, we tested multiple Python libraries to perform high-performance data processing and compared their effectiveness in terms of processing time, memory usage, peak memory, and throughput. Based on our evaluations, we can rank the libraries from best to least efficient as follows:

#### 1. Polars

- Best performance overall in terms of throughput (26,672.14 records/sec).
- Very fast due to Rust core, multi-threading, and lazy evaluation.
- Ideal for large-scale structured datasets.

### 2. Modin + Ray

- Great improvement over baseline, no need to change much code from pandas.
- Good CPU utilization with automatic parallelization.
- Slightly less efficient than Polars due to overhead from Ray.

### 3. Multiprocessing

- Effective CPU-bound task handling with custom control.
- Very flexible but requires careful management to avoid bugs.
- High throughput and memory savings.

#### 4. Joblib

- Easy implementation for parallelizing loops and repetitive tasks.
- Performed well for parsing tasks, moderate improvements across metrics.

### 5. Apache Spark

- Strong for distributed processing, but showed relatively lower throughput (2,588.22 records/sec) in our use case.
- High memory overhead due to Spark's architecture.
- More suitable for truly massive datasets (millions of rows or distributed clusters).

In terms of the full process (scraping  $\rightarrow$  cleaning  $\rightarrow$  optimization), we observed:

- Web scraping was stable after implementing Selenium with anti-bot tactics.
- Cleaning pipeline was highly customizable; however, apply() usage limited compatibility with some optimization frameworks.
- Optimization techniques drastically reduced processing time from ~109s to as low as ~5s (Polars), proving the value of choosing the right tool for scale.

### 8.2 Improvement to be done

For future enhancements, the following improvements are recommended:

- Refactor cleaning code to avoid apply(): The current usage of apply() limits compatibility with high-performance libraries (e.g., Dask, Vaex). Refactoring using vectorized operations or built-in functions would enhance performance and reduce processing time.
- Mixing libraries for faster web scraping: Currently, Selenium and BeautifulSoup were
  used sequentially, which can be slow for large-scale scraping. Combining libraries
  like Scrapy (for high-speed crawling), Playwright (for better dynamic rendering), or
  aiohttp with asyncio (for concurrent HTTP requests) can significantly improve
  scraping speed and efficiency.
- Use Dask with proper refactoring: Though Dask was skipped due to apply() limitations, refactoring the code would allow its integration, offering strong parallelism and scalability for very large datasets.
- Benchmark with larger datasets: Testing on a dataset with millions of rows would provide more realistic insights into how libraries like Spark and Dask perform under true high-load conditions.
- Explore hybrid optimization pipelines: Combining strengths of multiple libraries—e.g., using Polars for initial fast processing and Spark for distributed querying—could balance speed and scalability.
- Automate and scale scraping pipelines: Tools like Airflow or Kafka could help automate and manage continuous scraping tasks for real-time or large-scale applications.

Implementing these improvements would enable the system to handle more data at higher speeds, with better compatibility and efficiency across different processing stages.

## **Appendix**

Iproperty Website: <a href="https://www.iproperty.com.my/sale/all-residential/">https://www.iproperty.com.my/sale/all-residential/</a>

Data Scraping Google Colab:

 $\underline{https://colab.research.google.com/drive/13rqFmOfF7uuyUb1AsjxuVXrj2sjHaPgW?usp=sharing}$ 

SQLite + Data Cleaning Google Colab:

https://colab.research.google.com/drive/1\_jnPhfKX0OOMcsSbrDYIxRPJyHmyBOxP?usp=s haring

LogBook Github: <a href="https://github.com/users/Jingvong14/projects/3">https://github.com/users/Jingvong14/projects/3</a>

Lim Jing Yong Optimization (Modin + Ray) Google Colab:

https://colab.research.google.com/drive/1WthqdbUkXWVnRG9hnmNKKdJNTeTsuCX0?usp =sharing

Lee Soon Der Optimization (Polars) Google Colab:

https://colab.research.google.com/drive/1j-R06GOCs3sAsXz6-0qcLT0PFf6Ee\_jL?usp=sharing

Jaslene Yu Optimization (Multiprocessing + Spark) Google Colab:

https://colab.research.google.com/drive/1a91UY1zZKkCBuA-a6MSroimJ8VQv5TTN?usp=s haring

Nik Zulaikhaa Optimization (Joblib) Google Colab:

https://colab.research.google.com/drive/1SvnCFwGiOnF4mSEyzNy58V2jCziaZILW?usp=sharing

Visualization Google Colab:

https://colab.research.google.com/drive/1ETyMtF0aS4UgERg\_PK4iGFIvApjYB\_8o?usp=sh aring