TBD Phase 2: Performance & Computing Models

Introduction

In this lab, you will compare the performance and computing models of four popular data processing engines: **Polars, Pandas, DuckDB, and PySpark**.

You will explore:

- **Performance**: Single-node processing speed, parallel execution, and memory usage.
- **Scalability**: How performance changes with the number of cores (single-node) and executors (cluster).
- **Computing Models**: Out-of-core vs. In-memory processing, and Eager vs. Lazy execution.

Engine Capabilities

The following table summarizes the key capabilities of the engines we will be testing. Use this as a reference.

Engine	Query Optimizer	Distributed	Arrow-backed	Out-of-Core	Parallel	APIs	GPU Support
Pandas	□	□	optional ≥ 2.0	□	□	DataFrame	□
Polars	□	□	□	□	□	DataFrame	□ (opt)
PySpark	□	□	Pandas UDF/IO	□	□	SQL, DataFrame	□ (no GPU)
DuckDB	□	□	□	□	□	SQL, Relational API	□

Prerequisites

Ensure you have the necessary libraries installed.

```
!free -h

               total        used        free      shared  buff/cache
available
Mem:            15Gi       899Mi        13Gi       0.0Ki       1.2Gi
```

```
14Gi
Swap:              0B          0B          0B
```

```
!curl -s
"http://metadata.google.internal/computeMetadata/v1/instance/machine-
type" -H "Metadata-Flavor: Google"
```

```
projects/509446827198/machineTypes/e2-standard-4
```

```
%pip install polars pandas duckdb pyspark faker deltalake
memory_profiler pyarrow
```

```
Collecting polars
  Downloading polars-1.37.1-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: pandas in
/opt/conda/lib/python3.10/site-packages (2.3.3)
Collecting duckdb
  Downloading duckdb-1.4.3-cp310-cp310-
manylinux_2_26_x86_64.manylinux_2_28_x86_64.whl.metadata (4.3 kB)
Requirement already satisfied: pyspark in
/opt/conda/lib/python3.10/site-packages (4.0.1)
Collecting faker
  Downloading faker-40.1.2-py3-none-any.whl.metadata (16 kB)
Collecting deltalake
  Downloading deltalake-1.3.2-cp310-abi3-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (5.4 kB)
Collecting memory_profiler
  Downloading memory_profiler-0.61.0-py3-none-any.whl.metadata (20 kB)
Requirement already satisfied: pyarrow in
/opt/conda/lib/python3.10/site-packages (22.0.0)
Collecting polars-runtime-32==1.37.1 (from polars)
  Downloading polars_runtime_32-1.37.1-cp310-abi3-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (1.5 kB)
Requirement already satisfied: numpy>=1.22.4 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2.2.6)
Requirement already satisfied: python-dateutil>=2.8.2 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/opt/conda/lib/python3.10/site-packages (from pandas) (2025.3)
Requirement already satisfied: py4j==0.10.9.9 in
/opt/conda/lib/python3.10/site-packages (from pyspark) (0.10.9.9)
Collecting arro3-core>=0.5.0 (from deltalake)
  Downloading arro3_core-0.6.5-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (363 bytes)
Collecting deprecated>=1.2.18 (from deltalake)
  Downloading deprecated-1.3.1-py2.py3-none-any.whl.metadata (5.9 kB)
Requirement already satisfied: psutil in
/opt/conda/lib/python3.10/site-packages (from memory_profiler) (5.9.3)
```

```
Requirement already satisfied: typing-extensions in
/opt/conda/lib/python3.10/site-packages (from arro3-core>=0.5.0-
>deltalake) (4.15.0)
Requirement already satisfied: wrapt<3,>=1.10 in
/opt/conda/lib/python3.10/site-packages (from deprecated>=1.2.18-
>deltalake) (2.0.1)
Requirement already satisfied: six>=1.5 in
/opt/conda/lib/python3.10/site-packages (from python-dateutil>=2.8.2-
>pandas) (1.17.0)
Downloading polars-1.37.1-py3-none-any.whl (805 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 805.7/805.7 kB 32.1 MB/s
0:00:00
e_32-1.37.1-cp310-abi3-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(45.1 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 45.1/45.1 MB 83.6 MB/s
0:00:006m0:00:0100:01
anylinux_2_26_x86_64.manylinux_2_28_x86_64.whl (20.5 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20.5/20.5 MB 119.7 MB/s
0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.0/2.0 MB 84.1 MB/s  0:00:00
anylinux_2_17_x86_64.manylinux2014_x86_64.whl (37.7 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 37.7/37.7 MB 105.5 MB/s
0:00:00m0:00:01
emory_profiler-0.61.0-py3-none-any.whl (31 kB)
Downloading arro3_core-0.6.5-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (2.8 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.8/2.8 MB 94.3 MB/s  0:00:00
e-32, memory_profiler, faker, duckdb, deprecated, arro3-core, polars,
deltalake
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8/8 [deltalake]/8 [deltalake]
emory_profiler-0.61.0 polars-1.37.1 polars-runtime-32-1.37.1
Note: you may need to restart the kernel to use updated packages.
```

```
!sudo apt-get install -y openjdk-17-jdk
```

```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
The following additional packages will be installed:
  openjdk-17-jdk-headless openjdk-17-jre openjdk-17-jre-headless
Suggested packages:
  openjdk-17-demo openjdk-17-source visualvm libnss-mdns fonts-
ipafont-gothic
  fonts-ipafont-mincho fonts-wqy-microhei | fonts-wqy-zenhei fonts-
indic
The following NEW packages will be installed:
  openjdk-17-jdk openjdk-17-jdk-headless openjdk-17-jre
  openjdk-17-jre-headless
0 upgraded, 4 newly installed, 0 to remove and 32 not upgraded.
Need to get 116 MB of archives.
```

```
After this operation, 272 MB of additional disk space will be used.
Get:1 https://deb.debian.org/debian-security bullseye-security/main
amd64 openjdk-17-jre-headless amd64 17.0.17+10-1~deb11u1 [43.8 MB]
Get:2 https://deb.debian.org/debian-security bullseye-security/main
amd64 openjdk-17-jre amd64 17.0.17+10-1~deb11u1 [214 kB]
Get:3 https://deb.debian.org/debian-security bullseye-security/main
amd64 openjdk-17-jdk-headless amd64 17.0.17+10-1~deb11u1 [71.5 MB]
Get:4 https://deb.debian.org/debian-security bullseye-security/main
amd64 openjdk-17-jdk amd64 17.0.17+10-1~deb11u1 [10.5 kB]
Fetched 116 MB in 1s (94.5 MB/s)
Selecting previously unselected package openjdk-17-jre-headless:amd64.
(Reading database ... 148146 files and directories currently
installed.)
Preparing to unpack .../openjdk-17-jre-headless_17.0.17+10-
1~deb11u1_amd64.deb ...
Unpacking openjdk-17-jre-headless:amd64 (17.0.17+10-1~deb11u1) ...
Selecting previously unselected package openjdk-17-jre:amd64.
Preparing to unpack .../openjdk-17-jre_17.0.17+10-
1~deb11u1_amd64.deb ...
Unpacking openjdk-17-jre:amd64 (17.0.17+10-1~deb11u1) ...
Selecting previously unselected package openjdk-17-jdk-headless:amd64.
Preparing to unpack .../openjdk-17-jdk-headless_17.0.17+10-
1~deb11u1_amd64.deb ...
Unpacking openjdk-17-jdk-headless:amd64 (17.0.17+10-1~deb11u1) ...
Selecting previously unselected package openjdk-17-jdk:amd64.
Preparing to unpack .../openjdk-17-jdk_17.0.17+10-
1~deb11u1_amd64.deb ...
Unpacking openjdk-17-jdk:amd64 (17.0.17+10-1~deb11u1) ...
Setting up openjdk-17-jre-headless:amd64 (17.0.17+10-1~deb11u1) ...
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/java
to provide /usr/bin/java (java) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jpackage to provide
/usr/bin/jpackage (jpackage) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/keytool to provide
/usr/bin/keytool (keytool) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/rmiregistry to provide
/usr/bin/rmiregistry (rmiregistry) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/lib/jexec to provide /usr/bin/jexec
(jexec) in auto mode
Processing triggers for hicolor-icon-theme (0.17-2) ...
Processing triggers for ca-certificates-java
(20230710~deb12u1~deb11u1) ...
done.
Setting up openjdk-17-jdk-headless:amd64 (17.0.17+10-1~deb11u1) ...
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jar
```

```
to provide /usr/bin/jar (jar) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jarsigner to provide
/usr/bin/jarsigner (jarsigner) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/javac to provide /usr/bin/javac
(javac) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/javadoc to provide
/usr/bin/javadoc (javadoc) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/javap to provide /usr/bin/javap
(javap) in auto mode
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jcmd
to provide /usr/bin/jcmd (jcmd) in auto mode
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jdb
to provide /usr/bin/jdb (jdb) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jdeprscan to provide
/usr/bin/jdeprscan (jdeprscan) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jdeps to provide /usr/bin/jdeps
(jdeps) in auto mode
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jfr
to provide /usr/bin/jfr (jfr) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jimage to provide
/usr/bin/jimage (jimage) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jinfo to provide /usr/bin/jinfo
(jinfo) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jlink to provide /usr/bin/jlink
(jlink) in auto mode
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jmap
to provide /usr/bin/jmap (jmap) in auto mode
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jmod
to provide /usr/bin/jmod (jmod) in auto mode
update-alternatives: using /usr/lib/jvm/java-17-openjdk-amd64/bin/jps
to provide /usr/bin/jps (jps) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jrunscript to provide
/usr/bin/jrunscript (jrunscript) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jshell to provide
/usr/bin/jshell (jshell) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jstack to provide
/usr/bin/jstack (jstack) in auto mode
```

```
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jstat to provide /usr/bin/jstat
(jstat) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jstatd to provide
/usr/bin/jstatd (jstatd) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/serialver to provide
/usr/bin/serialver (serialver) in auto mode
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jhsdb to provide /usr/bin/jhsdb
(jhsdb) in auto mode
Setting up openjdk-17-jre:amd64 (17.0.17+10-1~deb11u1) ...
Setting up openjdk-17-jdk:amd64 (17.0.17+10-1~deb11u1) ...
update-alternatives: using
/usr/lib/jvm/java-17-openjdk-amd64/bin/jconsole to provide
/usr/bin/jconsole (jconsole) in auto mode
```

```python
import polars as pl
import pandas as pd
import duckdb
from pyspark.sql import SparkSession
from faker import Faker
import numpy as np
import os
import time
import psutil
from memory_profiler import memory_usage

# Initialize Spark (Single Node)
spark = SparkSession.builder \
    .appName("BigDataLab2") \
    .master("local[*]") \
    .config("spark.driver.memory", "4g") \
    .getOrCreate()
```

```
WARNING: Using incubator modules: jdk.incubator.vector
Using Spark's default log4j profile: org/apache/spark/log4j2-
defaults.properties
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use
setLogLevel(newLevel).
26/01/24 02:59:38 WARN NativeCodeLoader: Unable to load native-hadoop
library for your platform... using builtin-java classes where
applicable
```

```
!/usr/bin/java -version
```

```
openjdk version "17.0.17" 2025-10-21
OpenJDK Runtime Environment (build 17.0.17+10-Debian-1deb11u1)
```

```
OpenJDK 64-Bit Server VM (build 17.0.17+10-Debian-1deb11u1, mixed
mode, sharing)
```

Part 1: Data Generation

We will generate a synthetic dataset simulating social media posts with a rich schema.

Schema:

- `post_id` (String): Unique identifier.
- `user_id` (Integer): User identifier.
- `timestamp` (DateTime): Time of post.
- `content` (String): Text content.
- `likes` (Integer): Number of likes.
- `views` (Integer): Number of views.
- `category` (String): Post category.
- `tags` (List[String]): Hashtags.
- `location` (String): User location.
- `device` (String): Device used (Mobile, Web, etc.).
- `latency` (Float): Network latency.
- `error_rate` (Float): Error rate during upload.

```
def generate_data(num_records=1_000_000,
output_path="social_media_data.parquet"):
    fake = Faker()

    print(f"Generating {num_records} records...")

    # Generate data using numpy for speed where possible
    data = {
        "post_id": [fake.uuid4() for _ in range(num_records)],
        "user_id": np.random.randint(1, 100_000, num_records),
        "timestamp": pd.date_range(start="2023-01-01",
periods=num_records, freq="s").to_numpy().astype("datetime64[us]"),
        "likes": np.random.randint(0, 10_000, num_records),
        "views": np.random.randint(0, 1_000_000, num_records),
        "category": np.random.choice(["Tech", "Health", "Travel",
"Food", "Fashion", "Politics", "Sports"], num_records),
        "tags": [np.random.choice(["#viral", "#new", "#trending",
"#hot", "#update"], size=np.random.randint(1, 4)).tolist() for _ in
range(num_records)],
        "location": np.random.choice(["USA", "UK", "DE", "PL", "FR",
"JP", "BR"], num_records),
        "device": np.random.choice(["Mobile", "Desktop", "Tablet"],
num_records),
        "latency": np.random.uniform(10.0, 500.0, num_records),
        "error_rate": np.random.beta(1, 10, num_records),
        "content": [fake.sentence() for _ in range(min(num_records,
```

```python
1000))] * (num_records // 1000 + 1)
    }

    # Trim to exact size
    data["content"] = data["content"][:num_records]

    df = pd.DataFrame(data)

    print("Writing to Parquet...")
    df.to_parquet(output_path, engine="pyarrow")
    print(f"Data saved to {output_path}")

# Generate 5 million records
generate_data(num_records=5_000_000)
```

```
Generating 5000000 records...
Writing to Parquet...
Data saved to social_media_data.parquet
```

Part 2: Measuring Performance

2.1 Execution Time

Use `%time` or `%timeit` to measure execution time.

```python
# Example: Measuring time for all engines

print("--- Performance Benchmark Example ---")

# Pandas
print("Pandas Load Time:")
%time df_pd = pd.read_parquet("social_media_data.parquet")

# Polars
print("\nPolars Load Time:")
%time df_pl = pl.read_parquet("social_media_data.parquet")

# DuckDB
print("\nDuckDB Query Time:")
%time duckdb.sql("SELECT count(*) FROM
'social_media_data.parquet'").show()

# PySpark
print("\nSpark Load Time:")
%time df_spark = spark.read.parquet("social_media_data.parquet");
df_spark.count()
```

```
--- Performance Benchmark Example ---
Pandas Load Time:
```

```
CPU times: user 7.56 s, sys: 5.35 s, total: 12.9 s
Wall time: 8.28 s

Polars Load Time:
CPU times: user 1.25 s, sys: 1.24 s, total: 2.5 s
Wall time: 955 ms

DuckDB Query Time:
┌──────────────┐
│ count_star() │
│    int64     │
├──────────────┤
│      5000000 │
└──────────────┘

CPU times: user 8.82 ms, sys: 8.47 ms, total: 17.3 ms
Wall time: 7.75 ms

Spark Load Time:

[Stage 1:>                                                          (0
+ 4) / 4]

CPU times: user 18.8 ms, sys: 13.4 ms, total: 32.2 ms
Wall time: 8.82 s



5000000
```

Wyniki

Engine	Wall Time	Uwagi
DuckDB	7.75 ms	Najszybszy — tylko count, bez ładowania do pamięci
Polars	955 ms	Bardzo szybki load całego DataFrame
Pandas	8.28 s	~9x wolniejszy od Polars
Spark	8.82 s	Overhead inicjalizacji (single-node)

Part 3: Student Tasks

Task 1: Performance & Scalability (Single Node)

Goal: Benchmark the engines and test how they scale with available CPU cores.

Instructions:

1. **Define Queries**: Create 3 distinct queries of your own choice. They should cover:

    - **Query A**: A simple aggregation (e.g., grouping by a categorical column and calculating means).
    - **Query B**: A window function or more complex transformation.
    - **Query C**: A join (e.g., self-join or join with a smaller generated table) with filtering.
2. **Benchmark**: Implement these queries in **Pandas, Polars, DuckDB, and PySpark**.
    - Measure **Execution Time** using `%time` or `time.time()`.
    - Measure **Peak Memory** usage using `memory_profiler` (e.g., `memory_usage()`).
3. **Scalability Test**:
    - Select **all engines** that support parallel execution on a single node (e.g., Polars, DuckDB).
    - Run **all 3 queries** with different numbers of threads/cores (e.g., 1, 2, 4, 8).
    - Plot the speedup for each query and engine.

Tip:

- Polars: polars.thread_pool_size Please also note that *Thread configuration in Polars requires process restart*
- DuckDB: `PRAGMA threads=n`
- Spark: `master="local[n]"`

Query A: Agregacja (group by + mean)

```
# Query A: Grupowanie po category i obliczenie średnich
# Reinicjalizacja Spark (jeśli umarł)

try:

  spark.stop()

except:

  pass



from pyspark.sql import SparkSession



spark = SparkSession.builder \
    .appName("BigDataLab2") \
    .master("local[*]") \
    .config("spark.driver.memory", "4g") \
    .getOrCreate()
```

```
print("Spark restarted:", spark.version)

from memory_profiler import memory_usage

import time


PARQUET_PATH = "social_media_data.parquet"


print("=" * 60)

print("QUERY A: Agregacja (GROUP BY category -> mean likes, views)")

print("=" * 60)


# --- Pandas ---

def pandas_query_a():

  df = pd.read_parquet(PARQUET_PATH)

  return df.groupby("category").agg({"likes": "mean", "views":
"mean"})


print("\n[Pandas]")

mem_pandas = memory_usage((pandas_query_a,), max_usage=True,
retval=True)
%time result_pd = pandas_query_a()

print(f"Peak Memory: {mem_pandas[0]:.2f} MB")

print(result_pd)


# --- Polars ---

def polars_query_a():

  df = pl.read_parquet(PARQUET_PATH)

  return df.group_by("category").agg([
```

```
      pl.col("likes").mean().alias("avg_likes"),

      pl.col("views").mean().alias("avg_views")

  ])



print("\n[Polars]")

mem_polars = memory_usage((polars_query_a,), max_usage=True,
retval=True)
%time result_pl = polars_query_a()

print(f"Peak Memory: {mem_polars[0]:.2f} MB")

print(result_pl)



# --- DuckDB ---

def duckdb_query_a():

  return duckdb.sql(f"""

      SELECT category, AVG(likes) as avg_likes, AVG(views) as
avg_views
      FROM '{PARQUET_PATH}'

      GROUP BY category

  """).fetchdf()



print("\n[DuckDB]")

mem_duckdb = memory_usage((duckdb_query_a,), max_usage=True,
retval=True)
%time result_duck = duckdb_query_a()

print(f"Peak Memory: {mem_duckdb[0]:.2f} MB")

print(result_duck)



# --- PySpark ---

def spark_query_a():
```

```
  df = spark.read.parquet(PARQUET_PATH)

  return df.groupBy("category").agg({"likes": "mean", "views":
"mean"}).collect()


print("\n[PySpark]")

start = time.time()

result_spark = spark_query_a()

print(f"Wall time: {time.time() - start:.2f}s")

print(result_spark)
```

```
Spark restarted: 4.0.1
============================================================
QUERY A: Agregacja (GROUP BY category -> mean likes, views)
============================================================

[Pandas]
CPU times: user 7.86 s, sys: 1.71 s, total: 9.57 s
Wall time: 6.34 s
Peak Memory: 5180.17 MB
                likes          views
category
Fashion   5008.848463  499591.006376
Food      4998.607089  499996.339201
Health    4997.943025  500189.263137
Politics  5003.272542  500034.671918
Sports    4992.146781  500324.447201
Tech      5003.219720  500304.345136
Travel    5003.163856  500048.676321

[Polars]
CPU times: user 1.54 s, sys: 96.7 ms, total: 1.63 s
Wall time: 574 ms
Peak Memory: 3508.20 MB
shape: (7, 3)
┌──────────┬─────────────┬───────────────┐
│ category ┆ avg_likes   ┆ avg_views     │
│ ---      ┆ ---         ┆ ---           │
│ str      ┆ f64         ┆ f64           │
╞══════════╪═════════════╪═══════════════╡
│ Travel   ┆ 5003.163856 ┆ 500048.676321 │
│ Health   ┆ 4997.943025 ┆ 500189.263137 │
│ Food     ┆ 4998.607089 ┆ 499996.339201 │
│ Tech     ┆ 5003.21972  ┆ 500304.345136 │
```

```
│ Sports   ┆ 4992.146781 ┆ 500324.447201 │
│ Politics ┆ 5003.272542 ┆ 500034.671918 │
│ Fashion  ┆ 5008.848463 ┆ 499591.006376 │
└──────────┴─────────────┴───────────────┘

[DuckDB]
CPU times: user 293 ms, sys: 21.1 ms, total: 314 ms
Wall time: 97.1 ms
Peak Memory: 3237.06 MB
   category    avg_likes      avg_views
0    Health  4997.943025  500189.263137
1   Fashion  5008.848463  499591.006376
2    Sports  4992.146781  500324.447201
3    Travel  5003.163856  500048.676321
4  Politics  5003.272542  500034.671918
5      Food  4998.607089  499996.339201
6      Tech  5003.219720  500304.345136

[PySpark]

[Stage 1:===========================================>              (3
+ 1) / 4]

Wall time: 1.79s
[Row(category='Food', avg(views)=499996.3392013944,
avg(likes)=4998.607089312787), Row(category='Fashion',
avg(views)=499591.0063761093, avg(likes)=5008.8484631869915),
Row(category='Sports', avg(views)=500324.4472012756,
avg(likes)=4992.146780692146), Row(category='Travel',
avg(views)=500048.67632141605, avg(likes)=5003.163855728315),
Row(category='Health', avg(views)=500189.26313672116,
avg(likes)=4997.943025030803), Row(category='Tech',
avg(views)=500304.34513603133, avg(likes)=5003.219720143365),
Row(category='Politics', avg(views)=500034.6719178744,
avg(likes)=5003.27254174423)]
```

Wyniki Query A

Engine	Wall Time	Peak Memory	Uwagi
DuckDB	97.1 ms	3237 MB	Najszybszy, query pushdown
Polars	574 ms	3508 MB	~6x wolniejszy od DuckDB
PySpark	1.79 s	-	Przyzwoity na local mode
Pandas	6.34 s	5180 MB	Najwolniejszy,

Engine	Wall Time	Peak Memory	Uwagi
			najwięcej RAM

Query B: Window function - ranking użytkowników po likes w każdej kategorii

```
print("=" * 60)
print("QUERY B: Window Function (TOP 10 users by likes per category)")
print("=" * 60)

PARQUET_PATH = "social_media_data.parquet"

# --- Pandas ---
def pandas_query_b():
  df = pd.read_parquet(PARQUET_PATH)
  df['rank'] = df.groupby('category')['likes'].rank(method='dense',
ascending=False)
  return df[df['rank'] <= 10][['category', 'user_id', 'likes',
'rank']]

print("\n[Pandas]")
mem_pandas = memory_usage((pandas_query_b,), max_usage=True,
retval=True)
%time result_pd = pandas_query_b()
print(f"Peak Memory: {mem_pandas[0]:.2f} MB")
print(result_pd.head(10))

# --- Polars ---
def polars_query_b():
  df = pl.read_parquet(PARQUET_PATH)
  return df.with_columns(
      pl.col("likes").rank(method="dense",
descending=True).over("category").alias("rank")
  ).filter(pl.col("rank") <= 10).select(["category", "user_id",
"likes", "rank"])

print("\n[Polars]")
mem_polars = memory_usage((polars_query_b,), max_usage=True,
retval=True)
%time result_pl = polars_query_b()
print(f"Peak Memory: {mem_polars[0]:.2f} MB")
print(result_pl.head(10))

# --- DuckDB ---
def duckdb_query_b():
  return duckdb.sql(f"""
      SELECT category, user_id, likes, rank
      FROM (
          SELECT category, user_id, likes,
```

```
                DENSE_RANK() OVER (PARTITION BY category ORDER BY
likes DESC) as rank
          FROM '{PARQUET_PATH}'
      )
      WHERE rank <= 10
  """).fetchdf()

print("\n[DuckDB]")
mem_duckdb = memory_usage((duckdb_query_b,), max_usage=True,
retval=True)
%time result_duck = duckdb_query_b()
print(f"Peak Memory: {mem_duckdb[0]:.2f} MB")
print(result_duck.head(10))

# --- PySpark (bez memory_profiler) ---
from pyspark.sql.window import Window
from pyspark.sql.functions import dense_rank, col

def spark_query_b():
  df = spark.read.parquet(PARQUET_PATH)
  window = Window.partitionBy("category").orderBy(col("likes").desc())
  return df.withColumn("rank", dense_rank().over(window)) \
           .filter(col("rank") <= 10) \
           .select("category", "user_id", "likes", "rank") \
           .collect()

print("\n[PySpark]")
start = time.time()
result_spark = spark_query_b()
print(f"Wall time: {time.time() - start:.2f}s")
print(result_spark[:10])
```

```
============================================================
QUERY B: Window Function (TOP 10 users by likes per category)
============================================================

[Pandas]
CPU times: user 10.7 s, sys: 2.27 s, total: 13 s
Wall time: 10.1 s
Peak Memory: 5154.10 MB
      category  user_id  likes  rank
468     Health     5512   9991   9.0
1229      Tech    38752   9993   7.0
1574      Tech     4590   9991   9.0
1825    Sports    49813   9990  10.0
5400    Health    18689   9990  10.0
7733   Fashion    25174   9993   7.0
7952    Health    29721   9991   9.0
8759    Travel    55957   9993   7.0
9836      Tech    73491   9999   1.0
```

```
10374     Food    97445   9994   6.0

[Polars]
CPU times: user 2.66 s, sys: 189 ms, total: 2.85 s
Wall time: 972 ms
Peak Memory: 4292.53 MB
shape: (10, 4)
┌──────────┬──────────┬───────┬──────┐
│ category ┆ user_id  ┆ likes ┆ rank │
│ ---      ┆ ---      ┆ ---   ┆ ---  │
│ str      ┆ i64      ┆ i64   ┆ u32  │
╞══════════╪══════════╪═══════╪══════╡
│ Health   ┆ 5512     ┆ 9991  ┆ 9    │
│ Tech     ┆ 38752    ┆ 9993  ┆ 7    │
│ Tech     ┆ 4590     ┆ 9991  ┆ 9    │
│ Sports   ┆ 49813    ┆ 9990  ┆ 10   │
│ Health   ┆ 18689    ┆ 9990  ┆ 10   │
│ Fashion  ┆ 25174    ┆ 9993  ┆ 7    │
│ Health   ┆ 29721    ┆ 9991  ┆ 9    │
│ Travel   ┆ 55957    ┆ 9993  ┆ 7    │
│ Tech     ┆ 73491    ┆ 9999  ┆ 1    │
│ Food     ┆ 97445    ┆ 9994  ┆ 6    │
└──────────┴──────────┴───────┴──────┘

[DuckDB]
```

{"model_id":"91298be5cbe84af5b4e0c400c9c7749d","version_major":2,"version_minor":0}

{"model_id":"f40cc7b347794808bfbbd740bde25d05","version_major":2,"version_minor":0}

```
CPU times: user 6.91 s, sys: 99.1 ms, total: 7 s
Wall time: 2.25 s
Peak Memory: 4831.99 MB
  category  user_id  likes  rank
0     Tech    70030   9999     1
1     Tech    63540   9999     1
2     Tech    50099   9999     1
3     Tech    31839   9999     1
4     Tech    37219   9999     1
5     Tech    90402   9999     1
6     Tech    57954   9999     1
7     Tech    70612   9999     1
8     Tech    10294   9999     1
9     Tech    65836   9999     1

[PySpark]
```

```
[Stage 5:==============================================>             (3
+ 1) / 4]

Wall time: 8.74s
[Row(category='Fashion', user_id=81732, likes=9999, rank=1),
Row(category='Fashion', user_id=21305, likes=9999, rank=1),
Row(category='Fashion', user_id=42833, likes=9999, rank=1),
Row(category='Fashion', user_id=94459, likes=9999, rank=1),
Row(category='Fashion', user_id=39597, likes=9999, rank=1),
Row(category='Fashion', user_id=50875, likes=9999, rank=1),
Row(category='Fashion', user_id=19156, likes=9999, rank=1),
Row(category='Fashion', user_id=59856, likes=9999, rank=1),
Row(category='Fashion', user_id=51718, likes=9999, rank=1),
Row(category='Fashion', user_id=78709, likes=9999, rank=1)]
```

Wyniki Query B

Engine	Wall Time	Peak Memory	Uwagi
Polars	972 ms	4293 MB	Najszybszy, zoptymalizowane window functions
DuckDB	2.25 s	4832 MB	Dobry, ale wolniejszy niż Polars
PySpark	8.74 s	-	Shuffle przy partitionBy
Pandas	10.1 s	5154 MB	Najwolniejszy

Query C: Self-join - znajdź posty tego samego użytkownika z różnych urządzeń

```
print("=" * 60)
print("QUERY C: Join (posty tego samego usera z Mobile i Desktop)")
print("=" * 60)

PARQUET_PATH = "social_media_data.parquet"

# --- Pandas ---
def pandas_query_c():
  df = pd.read_parquet(PARQUET_PATH)
  mobile = df[df['device'] == 'Mobile'][['user_id', 'post_id',
'likes']].rename(columns={'post_id': 'mobile_post',
```

```
'likes': 'mobile_likes'})
  desktop = df[df['device'] == 'Desktop'][['user_id', 'post_id',
'likes']].rename(columns={'post_id': 'desktop_post',
'likes': 'desktop_likes'})
  return mobile.merge(desktop, on='user_id').head(1000)

print("\n[Pandas]")
mem_pandas = memory_usage((pandas_query_c,), max_usage=True,
retval=True)
%time result_pd = pandas_query_c()
print(f"Peak Memory: {mem_pandas[0]:.2f} MB")
print(f"Rows: {len(result_pd)}")
print(result_pd.head())

# --- Polars ---
def polars_query_c():
  df = pl.read_parquet(PARQUET_PATH)
  mobile = df.filter(pl.col('device') == 'Mobile').select(['user_id',
'post_id', 'likes']).rename({'post_id':
'mobile_post', 'likes': 'mobile_likes'})
  desktop = df.filter(pl.col('device') ==
'Desktop').select(['user_id', 'post_id', 'likes']).rename({'post_id':
'desktop_post', 'likes': 'desktop_likes'})
  return mobile.join(desktop, on='user_id').head(1000)

print("\n[Polars]")
mem_polars = memory_usage((polars_query_c,), max_usage=True,
retval=True)
%time result_pl = polars_query_c()
print(f"Peak Memory: {mem_polars[0]:.2f} MB")
print(f"Rows: {len(result_pl)}")
print(result_pl.head())

# --- DuckDB ---
def duckdb_query_c():
  return duckdb.sql(f"""
      SELECT m.user_id, m.post_id as mobile_post, m.likes as
mobile_likes,
             d.post_id as desktop_post, d.likes as desktop_likes
      FROM '{PARQUET_PATH}' m
      JOIN '{PARQUET_PATH}' d ON m.user_id = d.user_id
      WHERE m.device = 'Mobile' AND d.device = 'Desktop'
      LIMIT 1000
  """).fetchdf()

print("\n[DuckDB]")
mem_duckdb = memory_usage((duckdb_query_c,), max_usage=True,
retval=True)
%time result_duck = duckdb_query_c()
print(f"Peak Memory: {mem_duckdb[0]:.2f} MB")
```

```python
print(f"Rows: {len(result_duck)}")
print(result_duck.head())

# --- PySpark (bez memory_profiler) ---
from pyspark.sql.functions import col

def spark_query_c():
  df = spark.read.parquet(PARQUET_PATH)
  mobile = df.filter(col("device") == "Mobile").select(
      col("user_id"), col("post_id").alias("mobile_post"),
col("likes").alias("mobile_likes"))
  desktop = df.filter(col("device") == "Desktop").select(
      col("user_id"), col("post_id").alias("desktop_post"),
col("likes").alias("desktop_likes"))
  return mobile.join(desktop, "user_id").limit(1000).collect()

print("\n[PySpark]")
start = time.time()
result_spark = spark_query_c()
print(f"Wall time: {time.time() - start:.2f}s")
print(f"Rows: {len(result_spark)}")
print(result_spark[:5])
```

```
============================================================
QUERY C: Join (posty tego samego usera z Mobile i Desktop)
============================================================

[Pandas]
CPU times: user 28.5 s, sys: 4.26 s, total: 32.8 s
Wall time: 29.2 s
Peak Memory: 8655.23 MB
Rows: 1000
   user_id                           mobile_post  mobile_likes  \
0    64624  57ff3bbd-8411-4519-82fa-2acb58091dee           522
1    64624  57ff3bbd-8411-4519-82fa-2acb58091dee           522
2    64624  57ff3bbd-8411-4519-82fa-2acb58091dee           522
3    64624  57ff3bbd-8411-4519-82fa-2acb58091dee           522
4    64624  57ff3bbd-8411-4519-82fa-2acb58091dee           522

                           desktop_post  desktop_likes
0  a0c33ec9-90cc-499c-9563-b0121f9f5391           9024
1  75319c99-0510-4bdf-ad81-d392a59ca45a           7262
2  70925a6f-f9fb-4e3a-b48d-282338023e1c           6807
3  1bf7b54f-b832-4130-8a1e-d0d33c86321f           5838
4  1475d0eb-44e7-4730-a6be-2311748aa06c            613

[Polars]
CPU times: user 24.5 s, sys: 8.75 s, total: 33.3 s
Wall time: 18.1 s
Peak Memory: 10216.82 MB
```

```
Rows: 1000
shape: (5, 5)
┌──────────┬─────────────────────────────────┬──────────────┬─────────────────────────
─────────────────┬───────────────┐
│ user_id ┆ mobile_post                     ┆ mobile_likes ┆ desktop_post
┆ desktop_likes │
│ ---      ┆ ---                             ┆ ---          ┆ ---
┆ ---           │
│ i64      ┆ str                             ┆ i64          ┆ str
┆ i64           │
╞══════════╪═════════════════════════════════╪══════════════╪═════════════════════════
═════════════════╪═══════════════╡
│ 64624    ┆ 57ff3bbd-8411-4519-82fa-2a ┆ 522          ┆ a0c33ec9-90cc-
499c-9563-b0 ┆ 9024          │
│          ┆ cb58…                           ┆              ┆ 121f…
┆               │
│ 64624    ┆ 57ff3bbd-8411-4519-82fa-2a ┆ 522          ┆ 75319c99-0510-
4bdf-ad81-d3 ┆ 7262          │
│          ┆ cb58…                           ┆              ┆ 92a5…
┆               │
│ 64624    ┆ 57ff3bbd-8411-4519-82fa-2a ┆ 522          ┆ 70925a6f-f9fb-
4e3a-b48d-28 ┆ 6807          │
│          ┆ cb58…                           ┆              ┆ 2338…
┆               │
│ 64624    ┆ 57ff3bbd-8411-4519-82fa-2a ┆ 522          ┆ 1bf7b54f-b832-
4130-8a1e-d0 ┆ 5838          │
│          ┆ cb58…                           ┆              ┆ d33c…
┆               │
│ 64624    ┆ 57ff3bbd-8411-4519-82fa-2a ┆ 522          ┆ 1475d0eb-44e7-
4730-a6be-23 ┆ 613           │
│          ┆ cb58…                           ┆              ┆ 1174…
┆               │
└──────────┴─────────────────────────────────┴──────────────┴─────────────────────────
─────────────────┴───────────────┘

[DuckDB]
```

{"model_id":"97560e062667465487b15c3fb8e3a3fe","version_major":2,"version_minor":0}

```
CPU times: user 1.29 s, sys: 226 ms, total: 1.51 s
Wall time: 579 ms
Peak Memory: 13184.47 MB
Rows: 1000
   user_id                           mobile_post  mobile_likes  \
0    64624  57ff3bbd-8411-4519-82fa-2acb58091dee           522
1    38537  2dffa32a-6b65-4ec1-b849-d78696bc7032          3752
2    75342  dfce0829-1619-4efe-a02d-d31cfd50dfc4          9265
3    17166  c78cecbc-0af0-43e0-8a8f-ce292edb906e          1963
4     9810  a3600710-c140-4d00-8347-b571d8bd7b9b            46
```

```
                            desktop_post  desktop_likes
0  1bf7b54f-b832-4130-8a1e-d0d33c86321f          5838
1  0ae51952-a1e0-46b8-8682-5718f745a71d          3793
2  0d4d27cb-732c-495f-bf73-9b60c978bd8d             3
3  13d1a863-f515-4942-8ead-9eb5a19b3b42          7164
4  d47806b4-2b50-4409-98ee-7dd0caace49b          7808

[PySpark]



Wall time: 8.40s
Rows: 1000
[Row(user_id=6, mobile_post='1ee95c55-2e56-4bce-b579-7eb90d7d79e9', mobile_likes=3641, desktop_post='be391437-4078-4181-9a3d-4133615e0e8e', desktop_likes=1055), Row(user_id=6, mobile_post='1ee95c55-2e56-4bce-b579-7eb90d7d79e9', mobile_likes=3641, desktop_post='4afdf86d-e7d3-4d42-8c38-22eced32a4dc', desktop_likes=1769), Row(user_id=6, mobile_post='1ee95c55-2e56-4bce-b579-7eb90d7d79e9', mobile_likes=3641, desktop_post='9753c232-9fbd-480d-bf7f-0bb39be43dc0', desktop_likes=7470), Row(user_id=6, mobile_post='1ee95c55-2e56-4bce-b579-7eb90d7d79e9', mobile_likes=3641, desktop_post='b1147409-3f9a-419f-b098-f49798f9d006', desktop_likes=9009), Row(user_id=6, mobile_post='1ee95c55-2e56-4bce-b579-7eb90d7d79e9', mobile_likes=3641, desktop_post='4152f147-ddcf-4eae-8baf-2aa4d75684ff', desktop_likes=9243)]
```

Wyniki Query C

Engine	Wall Time	Peak Memory	Uwagi
DuckDB	579 ms	13184 MB	Najszybszy, query pushdown
Polars	18.1 s	10217 MB	~31x wolniejszy od DuckDB
Pandas	29.2 s	8655 MB	Najwolniejszy
PySpark	8.40 s	-	Shuffle overhead

Scalability test

```python
import matplotlib.pyplot as plt
import time

PARQUET_PATH = "social_media_data.parquet"
THREAD_COUNTS = [1, 2, 4]

# Wyniki: {engine: {query: {threads: time}}}
results = {
  'DuckDB': {'A': {}, 'B': {}, 'C': {}},
```

```python
    'Spark': {'A': {}, 'B': {}, 'C': {}}
}

# ============================================================
# DuckDB - można zmieniać threads dynamicznie
# ============================================================
print("=" * 60)
print("SCALABILITY TEST: DuckDB")
print("=" * 60)

def duckdb_query_a():
    return duckdb.sql(f"""
        SELECT category, AVG(likes) as avg_likes, AVG(views) as
avg_views
        FROM '{PARQUET_PATH}'
        GROUP BY category
    """).fetchdf()

def duckdb_query_b():
    return duckdb.sql(f"""
        SELECT category, user_id, likes, rank
        FROM (
            SELECT category, user_id, likes,
                   DENSE_RANK() OVER (PARTITION BY category ORDER BY
likes DESC) as rank
            FROM '{PARQUET_PATH}'
        )
        WHERE rank <= 10
    """).fetchdf()

def duckdb_query_c():
    return duckdb.sql(f"""
        SELECT m.user_id, m.post_id as mobile_post, m.likes as
mobile_likes,
               d.post_id as desktop_post, d.likes as desktop_likes
        FROM '{PARQUET_PATH}' m
        JOIN '{PARQUET_PATH}' d ON m.user_id = d.user_id
        WHERE m.device = 'Mobile' AND d.device = 'Desktop'
        LIMIT 1000
    """).fetchdf()

for threads in THREAD_COUNTS:
    print(f"\n[DuckDB threads={threads}]")
    duckdb.sql(f"PRAGMA threads={threads}")

    # Query A
    start = time.time()
    duckdb_query_a()
    results['DuckDB']['A'][threads] = time.time() - start
    print(f"  Query A: {results['DuckDB']['A'][threads]:.3f}s")
```

```
    # Query B
    start = time.time()
    duckdb_query_b()
    results['DuckDB']['B'][threads] = time.time() - start
    print(f"  Query B: {results['DuckDB']['B'][threads]:.3f}s")

    # Query C
    start = time.time()
    duckdb_query_c()
    results['DuckDB']['C'][threads] = time.time() - start
    print(f"  Query C: {results['DuckDB']['C'][threads]:.3f}s")

# ============================================================
# Spark - trzeba restartować sesję dla każdej konfiguracji
# ============================================================
print("\n" + "=" * 60)
print("SCALABILITY TEST: Spark")
print("=" * 60)

from pyspark.sql.window import Window
from pyspark.sql.functions import dense_rank, col

for threads in THREAD_COUNTS:
    print(f"\n[Spark local[{threads}]]")

    # Restart Spark z nową konfiguracją
    try:
        spark.stop()
    except:
        pass

    spark = SparkSession.builder \
        .appName("BigDataLab2") \
        .master(f"local[{threads}]") \
        .config("spark.driver.memory", "4g") \
        .getOrCreate()

    # Query A
    start = time.time()
    df = spark.read.parquet(PARQUET_PATH)
    df.groupBy("category").agg({"likes": "mean", "views":
"mean"}).collect()
    results['Spark']['A'][threads] = time.time() - start
    print(f"  Query A: {results['Spark']['A'][threads]:.3f}s")

    # Query B
    start = time.time()
    df = spark.read.parquet(PARQUET_PATH)
    window = Window.partitionBy("category").orderBy(col("likes").desc())
```

```
  df.withColumn("rank", dense_rank().over(window)) \
    .filter(col("rank") <= 10) \
    .select("category", "user_id", "likes", "rank") \
    .collect()
  results['Spark']['B'][threads] = time.time() - start
  print(f"  Query B: {results['Spark']['B'][threads]:.3f}s")

  # Query C
  start = time.time()
  df = spark.read.parquet(PARQUET_PATH)
  mobile = df.filter(col("device") == "Mobile").select(
      col("user_id"), col("post_id").alias("mobile_post"),
col("likes").alias("mobile_likes"))
  desktop = df.filter(col("device") == "Desktop").select(
      col("user_id"), col("post_id").alias("desktop_post"),
col("likes").alias("desktop_likes"))
  mobile.join(desktop, "user_id").limit(1000).collect()
  results['Spark']['C'][threads] = time.time() - start
  print(f"  Query C: {results['Spark']['C'][threads]:.3f}s")

# ============================================================
# WYKRESY
# ============================================================
print("\n" + "=" * 60)
print("PLOTTING RESULTS")
print("=" * 60)

fig, axes = plt.subplots(1, 3, figsize=(15, 5))
queries = ['A', 'B', 'C']
query_names = ['Query A (Aggregation)', 'Query B (Window)', 'Query C
(Join)']

for idx, (query, name) in enumerate(zip(queries, query_names)):
  ax = axes[idx]

  # DuckDB
  duckdb_times = [results['DuckDB'][query][t] for t in THREAD_COUNTS]
  duckdb_speedup = [duckdb_times[0] / t for t in duckdb_times]
  ax.plot(THREAD_COUNTS, duckdb_speedup, 'o-', label='DuckDB',
linewidth=2, markersize=8)

  # Spark
  spark_times = [results['Spark'][query][t] for t in THREAD_COUNTS]
  spark_speedup = [spark_times[0] / t for t in spark_times]
  ax.plot(THREAD_COUNTS, spark_speedup, 's-', label='Spark',
linewidth=2, markersize=8)

  # Idealna skalowalność
  ax.plot(THREAD_COUNTS, THREAD_COUNTS, '--', color='gray',
label='Ideal', alpha=0.5)
```

```python
  ax.set_xlabel('Threads')
  ax.set_ylabel('Speedup (vs 1 thread)')
  ax.set_title(name)
  ax.legend()
  ax.set_xticks(THREAD_COUNTS)
  ax.grid(True, alpha=0.3)

plt.tight_layout()
plt.savefig('scalability_test.png', dpi=150)
plt.show()

# Tabela wyników
print("\n--- RAW TIMES (seconds) ---")
print(f"{'Engine':<10} {'Query':<8} " + " ".join([f"{t}T" for t in THREAD_COUNTS]))
for engine in ['DuckDB', 'Spark']:
  for query in queries:
      times = [f"{results[engine][query][t]:.3f}" for t in THREAD_COUNTS]
      print(f"{engine:<10} {query:<8} " + " ".join(times))

print("\nNote: Polars wymaga restartu kernela dla zmiany liczby wątków - pominięty w teście.")
```

```
============================================================
SCALABILITY TEST: DuckDB
============================================================

[DuckDB threads=1]
  Query A: 1.693s
```

{"model_id":"07dd19ee1de545dc9574372ae0351063","version_major":2,"version_minor":0}

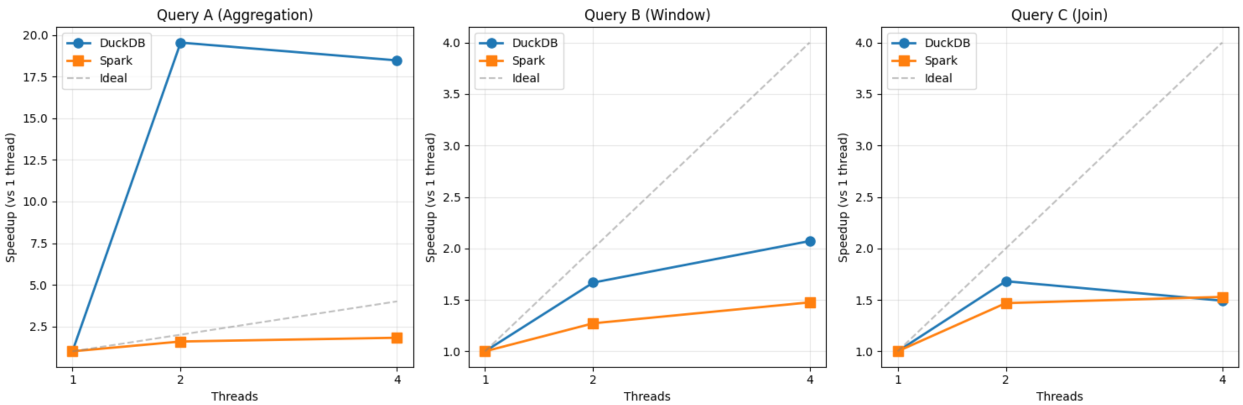
```
  Query B: 4.562s
  Query C: 0.881s

[DuckDB threads=2]
  Query A: 0.087s
```

{"model_id":"697c7e9503a0422eacf6eaecde6ae020","version_major":2,"version_minor":0}

```
  Query B: 2.735s
  Query C: 0.524s

[DuckDB threads=4]
  Query A: 0.092s
```

{"model_id":"bc4f8c86805f421eb5062e6d1794d78a","version_major":2,"version_minor":0}

```
  Query B: 2.202s
  Query C: 0.590s

============================================================
SCALABILITY TEST: Spark
============================================================

[Spark local[1]]

  Query A: 2.176s

  Query B: 12.709s

  Query C: 8.023s

[Spark local[2]]

  Query A: 1.368s

  Query B: 9.990s

  Query C: 5.463s

[Spark local[4]]

  Query A: 1.199s

  Query B: 8.613s

  Query C: 5.247s

============================================================
PLOTTING RESULTS
============================================================
```




```
--- RAW TIMES (seconds) ---
Engine     Query    1T 2T 4T
DuckDB     A        1.693 0.087 0.092
DuckDB     B        4.562 2.735 2.202
DuckDB     C        0.881 0.524 0.590
Spark      A        2.176 1.368 1.199
Spark      B        12.709 9.990 8.613
Spark      C        8.023 5.463 5.247

Note: Polars wymaga restartu kernela dla zmiany liczby wątków -
pominięty w teście.
```

Wyniki Scalability test

Engine	Query	1T	2T	4T
DuckDB	A	1.693	0.087	0.092
DuckDB	B	4.562	2.735	2.202
DuckDB	C	0.881	0.524	0.590
Spark	A	2.176	1.368	1.199
Spark	B	12.709	9.990	8.613
Spark	C	8.023	5.463	5.247

Polars wymaga restartu kernela dla zmiany liczby wątków - pominięty w teście.

Task 2: Spark on Cluster

Goal: Compare Single Node performance vs. Spark on a Cluster.

Instructions:

1. **Infrastructure**: Use the infrastructure from **Phase 1** (Google Dataproc). You may need to modify your Terraform code to adjust the cluster configuration (e.g., number of worker nodes).
2. **Environment**: The easiest way to run this is via **Google Workbench** connected to your Dataproc cluster.

3. **Upload Data**: Upload the generated `social_media_data.parquet` to HDFS or GCS.
   – **Tip**: For better performance, consider **partitioning** the data (e.g., by `category` or `date`) when saving it to the distributed storage. This allows Spark to optimize reads.
4. **Run Queries**: Run your PySpark queries from Task 1 on the cluster.
5. **Scalability Test**:
   – Run the queries with different numbers of **worker nodes** (e.g., 2, 3, 4).
   – You can achieve this by resizing the cluster (manually or via Terraform) or by configuring the number of executors in Spark.
6. **Analyze**:
   – How does the cluster performance compare to your local machine?
   – Did adding more nodes/executors linearly improve performance?
   – **Tip**: If Spark is slower than single-node engines, consider **increasing the dataset size** (e.g., generate 10M+ records or duplicate the data). Spark's overhead is significant for small data, and its true power appears when data exceeds single-node memory.

```
!gsutil cp social_media_data.parquet gs://tbd-2025z-347430-
conf/social_media_data.parquet

Copying file://social_media_data.parquet
[Content-Type=application/octet-stream]...
==> NOTE: You are uploading one or more large file(s), which would run

significantly faster if you enable parallel composite uploads. This
feature can be enabled by editing the
"parallel_composite_upload_threshold" value in your .boto
configuration file. However, note that if you do this large files will
be uploaded as `composite objects
<https://cloud.google.com/storage/docs/composite-objects>`_,which
means that any user who downloads such objects will need to have a
compiled crcmod installed (see "gsutil help crcmod"). This is because
without a compiled crcmod, computing checksums on composite objects is
so slow that gsutil disables downloads of composite objects.

- [1 files][335.5 MiB/335.5 MiB]

Operation completed over 1 objects/335.5 MiB.

26/01/24 03:57:43 WARN JavaUtils: Attempt to delete using native Unix
OS command failed for path = /tmp/blockmgr-49d237e6-2d62-4dc8-aa20-
a8106cda7db5. Falling back to Java IO way
java.io.IOException: Failed to delete: /tmp/blockmgr-49d237e6-2d62-
4dc8-aa20-a8106cda7db5
	at
org.apache.spark.network.util.JavaUtils.deleteRecursivelyUsingUnixNati
ve(JavaUtils.java:199)
	at
org.apache.spark.network.util.JavaUtils.deleteRecursively(JavaUtils.ja
```

```
va:116)
      at
org.apache.spark.network.util.JavaUtils.deleteRecursively(JavaUtils.ja
va:94)
      at
org.apache.spark.util.SparkFileUtils.deleteRecursively(SparkFileUtils.
scala:121)
      at org.apache.spark.util.SparkFileUtils.deleteRecursively$
(SparkFileUtils.scala:120)
      at
org.apache.spark.util.Utils$.deleteRecursively(Utils.scala:1048)
      at org.apache.spark.storage.DiskBlockManager.
$anonfun$doStop$1(DiskBlockManager.scala:372)
      at org.apache.spark.storage.DiskBlockManager.
$anonfun$doStop$1$adapted(DiskBlockManager.scala:368)
      at
scala.collection.ArrayOps$.foreach$extension(ArrayOps.scala:1324)
      at
org.apache.spark.storage.DiskBlockManager.doStop(DiskBlockManager.scal
a:368)
      at
org.apache.spark.storage.DiskBlockManager.stop(DiskBlockManager.scala:
363)
      at
org.apache.spark.storage.BlockManager.stop(BlockManager.scala:2166)
      at org.apache.spark.SparkEnv.stop(SparkEnv.scala:118)
      at org.apache.spark.SparkContext.
$anonfun$stop$25(SparkContext.scala:2395)
      at
org.apache.spark.util.Utils$.tryLogNonFatalError(Utils.scala:1300)
      at org.apache.spark.SparkContext.stop(SparkContext.scala:2395)
      at org.apache.spark.SparkContext.stop(SparkContext.scala:2297)
      at org.apache.spark.SparkContext.
$anonfun$new$36(SparkContext.scala:704)
      at
org.apache.spark.util.SparkShutdownHook.run(ShutdownHookManager.scala:
231)
      at org.apache.spark.util.SparkShutdownHookManager.
$anonfun$runAll$2(ShutdownHookManager.scala:205)
      at
scala.runtime.java8.JFunction0$mcV$sp.apply(JFunction0$mcV$sp.scala:18
)
      at
org.apache.spark.util.Utils$.logUncaughtExceptions(Utils.scala:1937)
      at org.apache.spark.util.SparkShutdownHookManager.
$anonfun$runAll$1(ShutdownHookManager.scala:205)
      at
scala.runtime.java8.JFunction0$mcV$sp.apply(JFunction0$mcV$sp.scala:18
)
```

```
        at scala.util.Try$.apply(Try.scala:217)
        at
org.apache.spark.util.SparkShutdownHookManager.runAll(ShutdownHookMana
ger.scala:205)
        at org.apache.spark.util.SparkShutdownHookManager$
$anon$2.run(ShutdownHookManager.scala:184)
        at
java.base/java.util.concurrent.Executors$RunnableAdapter.call(Executor
s.java:539)
        at
java.base/java.util.concurrent.FutureTask.run(FutureTask.java:264)
        at
java.base/java.util.concurrent.ThreadPoolExecutor.runWorker(ThreadPool
Executor.java:1136)
        at
java.base/java.util.concurrent.ThreadPoolExecutor$Worker.run(ThreadPoo
lExecutor.java:635)
        at java.base/java.lang.Thread.run(Thread.java:840)
```

```python
# Kernel: PySpark on tbd-cluster (Remote)

from pyspark.sql import SparkSession
from pyspark.sql.window import Window
from pyspark.sql.functions import dense_rank, col
import time

# Spark powinien być już zainicjalizowany przez kernel
print("Spark version:", spark.version)
print("Spark master:", spark.sparkContext.master)

GCS_PATH = "gs://tbd-2025z-347430-conf/social_media_data.parquet"

df = spark.read.parquet(GCS_PATH)
print(f"Records: {df.count()}")

print("=" * 60)
print("TASK 2: Spark on Dataproc Cluster")
print("=" * 60)

# --- Query A: Aggregation ---
print("\n[Query A: Aggregation]")
start = time.time()
result_a = df.groupBy("category").agg({"likes": "mean", "views":
"mean"}).collect()
time_a = time.time() - start
print(f"Wall time: {time_a:.2f}s")
print(result_a)

# --- Query B: Window Function ---
print("\n[Query B: Window Function]")
```

```
start = time.time()
window = Window.partitionBy("category").orderBy(col("likes").desc())
result_b = df.withColumn("rank", dense_rank().over(window)) \
           .filter(col("rank") <= 10) \
           .select("category", "user_id", "likes", "rank") \
           .collect()
time_b = time.time() - start
print(f"Wall time: {time_b:.2f}s")
print(result_b[:10])

# --- Query C: Join ---
print("\n[Query C: Join]")
start = time.time()
mobile = df.filter(col("device") == "Mobile").select(
  col("user_id"), col("post_id").alias("mobile_post"),
col("likes").alias("mobile_likes"))
desktop = df.filter(col("device") == "Desktop").select(
  col("user_id"), col("post_id").alias("desktop_post"),
col("likes").alias("desktop_likes"))
result_c = mobile.join(desktop, "user_id").limit(1000).collect()
time_c = time.time() - start
print(f"Wall time: {time_c:.2f}s")
print(f"Rows: {len(result_c)}")

# --- Podsumowanie ---
print("\n" + "=" * 60)
print("SUMMARY: Spark Cluster vs Local")
print("=" * 60)
print(f"Query A (Aggregation): {time_a:.2f}s")
print(f"Query B (Window):      {time_b:.2f}s")
print(f"Query C (Join):        {time_c:.2f}s")
```

```
Spark version: 3.5.3
Spark master: yarn



Records: 5000000
============================================================
TASK 2: Spark on Dataproc Cluster
============================================================

[Query A: Aggregation]



Wall time: 10.30s
[Row(category='Food', avg(views)=499996.3392013944,
avg(likes)=4998.607089312787), Row(category='Sports',
avg(views)=500324.4472012756, avg(likes)=4992.146780692146),
Row(category='Tech', avg(views)=500304.34513603133,
```

```
avg(likes)=5003.219720143365), Row(category='Fashion',
avg(views)=499591.0063761093, avg(likes)=5008.8484631869915),
Row(category='Travel', avg(views)=500048.67632141605,
avg(likes)=5003.163855728315), Row(category='Health',
avg(views)=500189.26313672116, avg(likes)=4997.943025030803),
Row(category='Politics', avg(views)=500034.6719178744,
avg(likes)=5003.27254174423)]

[Query B: Window Function]



Wall time: 26.46s
[Row(category='Fashion', user_id=81732, likes=9999, rank=1),
Row(category='Fashion', user_id=21305, likes=9999, rank=1),
Row(category='Fashion', user_id=42833, likes=9999, rank=1),
Row(category='Fashion', user_id=94459, likes=9999, rank=1),
Row(category='Fashion', user_id=39597, likes=9999, rank=1),
Row(category='Fashion', user_id=50875, likes=9999, rank=1),
Row(category='Fashion', user_id=19156, likes=9999, rank=1),
Row(category='Fashion', user_id=59856, likes=9999, rank=1),
Row(category='Fashion', user_id=51718, likes=9999, rank=1),
Row(category='Fashion', user_id=78709, likes=9999, rank=1)]

[Query C: Join]

[Stage 14:>                                                          (0
+ 1) / 1]

Wall time: 20.85s
Rows: 1000

============================================================
SUMMARY: Spark Cluster vs Local
============================================================
Query A (Aggregation): 10.30s
Query B (Window):      26.46s
Query C (Join):        20.85s

26/01/24 04:04:31 ERROR AsyncEventQueue: Listener EventLoggingListener
threw an exception
java.lang.NullPointerException: null
      at
com.google.cloud.hadoop.fs.gcs.GoogleHadoopFileSystem.getGcsFs(GoogleH
adoopFileSystem.java:1713) ~[gcs-connector-3.0.13.jar:?]
      at
com.google.cloud.hadoop.fs.gcs.GoogleHadoopOutputStream.commitTempFile
(GoogleHadoopOutputStream.java:379) ~[gcs-connector-3.0.13.jar:?]
      at
com.google.cloud.hadoop.fs.gcs.GoogleHadoopOutputStream.hsyncInternal(
GoogleHadoopOutputStream.java:333) ~[gcs-connector-3.0.13.jar:?]
```

```
	at
com.google.cloud.hadoop.fs.gcs.GoogleHadoopOutputStream.lambda$hflush$
2(GoogleHadoopOutputStream.java:294) ~[gcs-connector-3.0.13.jar:?]
	at
org.apache.hadoop.fs.statistics.impl.IOStatisticsBinding.invokeTrackin
gDuration(IOStatisticsBinding.java:547) ~[hadoop-client-api-
3.3.6.jar:?]
	at
org.apache.hadoop.fs.statistics.impl.IOStatisticsBinding.lambda$trackD
urationOfOperation$5(IOStatisticsBinding.java:528) ~[hadoop-client-
api-3.3.6.jar:?]
	at
org.apache.hadoop.fs.statistics.impl.IOStatisticsBinding.trackDuration
(IOStatisticsBinding.java:449) ~[hadoop-client-api-3.3.6.jar:?]
	at
com.google.cloud.hadoop.fs.gcs.GhfsGlobalStorageStatistics.trackDurati
on(GhfsGlobalStorageStatistics.java:117) ~[gcs-connector-3.0.13.jar:?]
	at
com.google.cloud.hadoop.fs.gcs.GoogleHadoopOutputStream.trackDurationW
ithTracing(GoogleHadoopOutputStream.java:249) ~[gcs-connector-
3.0.13.jar:?]
	at
com.google.cloud.hadoop.fs.gcs.GoogleHadoopOutputStream.hflush(GoogleH
adoopOutputStream.java:280) ~[gcs-connector-3.0.13.jar:?]
	at
org.apache.hadoop.fs.FSDataOutputStream.hflush(FSDataOutputStream.java
:136) ~[hadoop-client-api-3.3.6.jar:?]
	at org.apache.spark.deploy.history.EventLogFileWriter.
$anonfun$writeLine$3(EventLogFileWriters.scala:122) ~[spark-core_2.12-
3.5.3.jar:3.5.3]
	at org.apache.spark.deploy.history.EventLogFileWriter.
$anonfun$writeLine$3$adapted(EventLogFileWriters.scala:122) ~[spark-
core_2.12-3.5.3.jar:3.5.3]
	at scala.Option.foreach(Option.scala:407) ~[scala-library-
2.12.18.jar:?]
	at
org.apache.spark.deploy.history.EventLogFileWriter.writeLine(EventLogF
ileWriters.scala:122) ~[spark-core_2.12-3.5.3.jar:3.5.3]
	at
org.apache.spark.deploy.history.SingleEventLogFileWriter.writeEvent(Ev
entLogFileWriters.scala:229) ~[spark-core_2.12-3.5.3.jar:3.5.3]
	at
org.apache.spark.scheduler.EventLoggingListener.logEvent(EventLoggingL
istener.scala:97) ~[spark-core_2.12-3.5.3.jar:3.5.3]
	at
org.apache.spark.scheduler.EventLoggingListener.onApplicationEnd(Event
LoggingListener.scala:181) ~[spark-core_2.12-3.5.3.jar:3.5.3]
	at
org.apache.spark.scheduler.SparkListenerBus.doPostEvent(SparkListenerB
```

```
us.scala:57) ~[spark-core_2.12-3.5.3.jar:3.5.3]
      at org.apache.spark.scheduler.SparkListenerBus.doPostEvent$
(SparkListenerBus.scala:28) ~[spark-core_2.12-3.5.3.jar:3.5.3]
      at
org.apache.spark.scheduler.AsyncEventQueue.doPostEvent(AsyncEventQueue
.scala:37) ~[spark-core_2.12-3.5.3.jar:3.5.3]
      at
org.apache.spark.scheduler.AsyncEventQueue.doPostEvent(AsyncEventQueue
.scala:37) ~[spark-core_2.12-3.5.3.jar:3.5.3]
      at
org.apache.spark.util.ListenerBus.postToAll(ListenerBus.scala:117)
~[spark-core_2.12-3.5.3.jar:3.5.3]
      at org.apache.spark.util.ListenerBus.postToAll$
(ListenerBus.scala:101) ~[spark-core_2.12-3.5.3.jar:3.5.3]
      at
org.apache.spark.scheduler.AsyncEventQueue.super$postToAll(AsyncEventQ
ueue.scala:105) ~[spark-core_2.12-3.5.3.jar:3.5.3]
      at org.apache.spark.scheduler.AsyncEventQueue.
$anonfun$dispatch$1(AsyncEventQueue.scala:105) ~[spark-core_2.12-
3.5.3.jar:3.5.3]
      at
scala.runtime.java8.JFunction0$mcJ$sp.apply(JFunction0$mcJ$sp.java:23)
~[scala-library-2.12.18.jar:?]
      at scala.util.DynamicVariable.withValue(DynamicVariable.scala:62)
~[scala-library-2.12.18.jar:?]
      at
org.apache.spark.scheduler.AsyncEventQueue.org$apache$spark$scheduler$
AsyncEventQueue$$dispatch(AsyncEventQueue.scala:100) ~[spark-
core_2.12-3.5.3.jar:3.5.3]
      at org.apache.spark.scheduler.AsyncEventQueue$
$anon$2.$anonfun$run$1(AsyncEventQueue.scala:96) ~[spark-core_2.12-
3.5.3.jar:3.5.3]
      at
org.apache.spark.util.Utils$.tryOrStopSparkContext(Utils.scala:1358)
[spark-core_2.12-3.5.3.jar:3.5.3]
      at org.apache.spark.scheduler.AsyncEventQueue$
$anon$2.run(AsyncEventQueue.scala:96) [spark-core_2.12-
3.5.3.jar:3.5.3]
```

Wyniki dla Pyspark local vs cluster lda 5_000_000 rekordów

Query	Spark Local (4T)	Spark Cluster	Różnica
A (Aggregation)	1.79s	10.30s	5.8x wolniej
B (Window)	8.74s	26.46s	3.0x wolniej
C (Join)	8.40s	20.85s	2.5x wolniej

Task 3: Execution Modes & Analysis

Goal: Deep dive into execution models and limitations.

Instructions:

1. **Lazy vs. Eager vs. Streaming**:
   - Use **Polars**. Compare the **Execution Time** and **Peak Memory** of:
     - Eager execution (`read_parquet` -> filter).
     - Lazy execution (`scan_parquet` -> filter -> `collect()`).
     - Streaming execution (`scan_parquet` -> filter -> `collect(streaming=True)`).
2. **Polars Limitations**:
   - Identify a scenario where Polars might struggle compared to Spark (e.g., memory limits).
3. **Decision Boundary**:
   - Based on your findings, when would you recommend switching from a single-node tool (Polars/DuckDB) to a distributed engine (Spark)?

```
# Kernel: Python 3 (ipykernel) (Local)

import polars as pl
import time
from memory_profiler import memory_usage

PARQUET_PATH = "social_media_data.parquet"

print("=" * 60)
print("TASK 3: Lazy vs Eager vs Streaming (Polars)")
print("=" * 60)

# Filtr testowy: kategoria = 'Tech' i likes > 5000
FILTER_CATEGORY = "Tech"
FILTER_LIKES = 5000

# --- 1. EAGER execution ---
def eager_execution():
  df = pl.read_parquet(PARQUET_PATH)  # Wczytuje całość do RAM
  result = df.filter((pl.col("category") == FILTER_CATEGORY) &
(pl.col("likes") > FILTER_LIKES))
  return result

print("\n[1. EAGER: read_parquet -> filter]")
start = time.time()
mem_eager = memory_usage((eager_execution,), max_usage=True,
retval=True)
eager_time = time.time() - start
print(f"Wall time: {eager_time:.3f}s")
print(f"Peak Memory: {mem_eager[0]:.2f} MB")
print(f"Rows: {len(mem_eager[1])}")

# --- 2. LAZY execution ---
def lazy_execution():
```

```
  df = pl.scan_parquet(PARQUET_PATH)  # Nie wczytuje, tylko plan
  result = df.filter((pl.col("category") == FILTER_CATEGORY) &
(pl.col("likes") > FILTER_LIKES))
  return result.collect()  # Wykonuje zoptymalizowany plan

print("\n[2. LAZY: scan_parquet -> filter -> collect()]")
start = time.time()
mem_lazy = memory_usage((lazy_execution,), max_usage=True,
retval=True)
lazy_time = time.time() - start
print(f"Wall time: {lazy_time:.3f}s")
print(f"Peak Memory: {mem_lazy[0]:.2f} MB")
print(f"Rows: {len(mem_lazy[1])}")

# --- 3. STREAMING execution ---
def streaming_execution():
  df = pl.scan_parquet(PARQUET_PATH)
  result = df.filter((pl.col("category") == FILTER_CATEGORY) &
(pl.col("likes") > FILTER_LIKES))
  return result.collect(streaming=True)  # Przetwarza w chunkach

print("\n[3. STREAMING: scan_parquet -> filter ->
collect(streaming=True)]")
start = time.time()
mem_streaming = memory_usage((streaming_execution,), max_usage=True,
retval=True)
streaming_time = time.time() - start
print(f"Wall time: {streaming_time:.3f}s")
print(f"Peak Memory: {mem_streaming[0]:.2f} MB")
print(f"Rows: {len(mem_streaming[1])}")

# --- PODSUMOWANIE ---
print("\n" + "=" * 60)
print("SUMMARY: Execution Modes")
print("=" * 60)
print(f"{'Mode':<12} {'Time':<10} {'Peak Memory':<15}")
print(f"{'Eager':<12} {eager_time:.3f}s     {mem_eager[0]:.0f} MB")
print(f"{'Lazy':<12} {lazy_time:.3f}s     {mem_lazy[0]:.0f} MB")
print(f"{'Streaming':<12} {streaming_time:.3f}s
{mem_streaming[0]:.0f} MB")
```

```
============================================================
TASK 3: Lazy vs Eager vs Streaming (Polars)
============================================================

[1. EAGER: read_parquet -> filter]
Wall time: 2.445s
Peak Memory: 1743.05 MB
Rows: 358395
```

```
[2. LAZY: scan_parquet -> filter -> collect()]
Wall time: 1.115s
Peak Memory: 2127.31 MB
Rows: 358395

[3. STREAMING: scan_parquet -> filter -> collect(streaming=True)]

/var/tmp/ipykernel_33882/2858808293.py:49: DeprecationWarning: the
`streaming` parameter was deprecated in 1.25.0; use `engine` instead.
  return result.collect(streaming=True)  # Przetwarza w chunkach

Wall time: 1.121s
Peak Memory: 2431.97 MB
Rows: 358395

============================================================
SUMMARY: Execution Modes
============================================================
Mode         Time       Peak Memory
Eager        2.445s     1743 MB
Lazy         1.115s     2127 MB
Streaming    1.121s     2432 MB
```

Polars nie przetworzy 500GB pliku na maszynie z 32GB RAM — Spark rozłoży to na klaster i obsłuży bez problemu.

Lazy/Eager/Streaming Polars - Wyniki

Mode	Time	Peak Memory	Uwagi
Eager	2.445s	1743 MB	Wczytuje całość, potem filtruje
Lazy	1.115s	2127 MB	Query optimization, predicate pushdown
Streaming	1.121s	2432 MB	Przetwarza w chunkach

When to switch from single node solution?

Polecałbym przejście z rozwiązania single-node na PySpark na klastrze gdy dane są zbyt duże, by zmieścić się w RAM jednej maszyny, lub gdy przetwarzanie rozproszone na wielu nodach będzie szybsze niż lokalne.