\Orchestrating a brighter world

Accelerate Pandas Scripts with 1 Line of Code (FireDucks)

Aug 26, 2024

Sourav Saha (NEC)

Agenda

Quick Introduction!

SOURAV SAHA – Research Engineer @ NEC Corporation

https://www.linkedin.com/in/sourav-%E3%82%BD%E3%82%A6%E3%83%A9%E3%83%96-saha-%E3%82%B5%E3%83%8F-a5750259/

https://twitter.com/SouravSaha97589

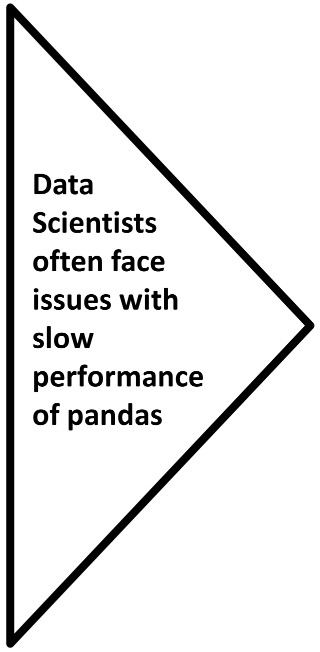
Hello, I am a software professional with 11+ years of working experience across diverse areas of **HPC, Vector Supercomputing, Distributed Programming, Big Data and Machine Learning**. Currently, my team at NEC R&D Lab, Japan, is researching various data processing-related algorithms. Blending the mixture of different niche technologies related to compiler framework, high-performance computing, and multi-threaded programming, we have developed a Python library named FireDucks with highly compatible pandas APIs for DataFrame-related operations.

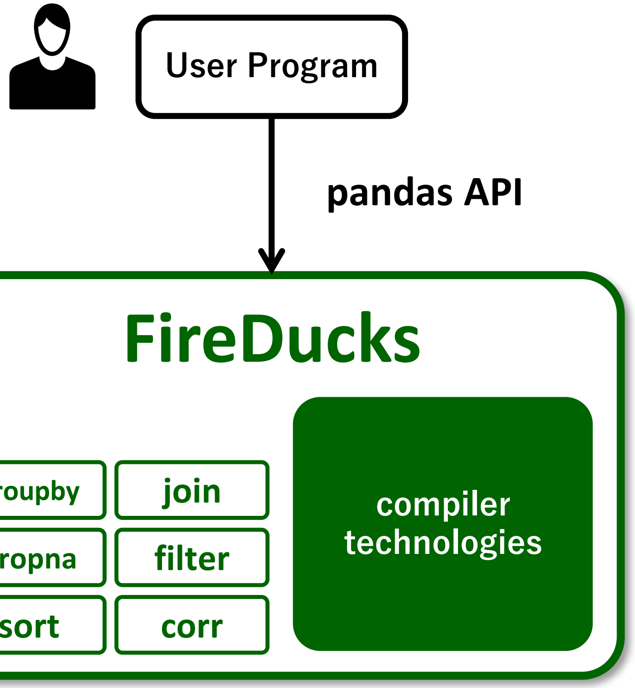
https://www.nec.com/en/global/solutions/hpc/sx/index.html

Mr. Kazuhisa Ishizaka (Primary Author)

we wanted to develop some library using compiler technology

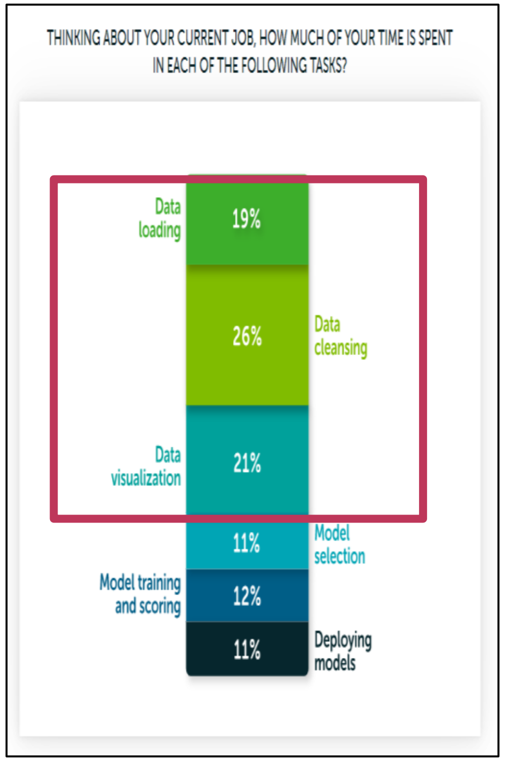
we wanted to speed-up python


Data Scientists often face issues with slow performance of pandas

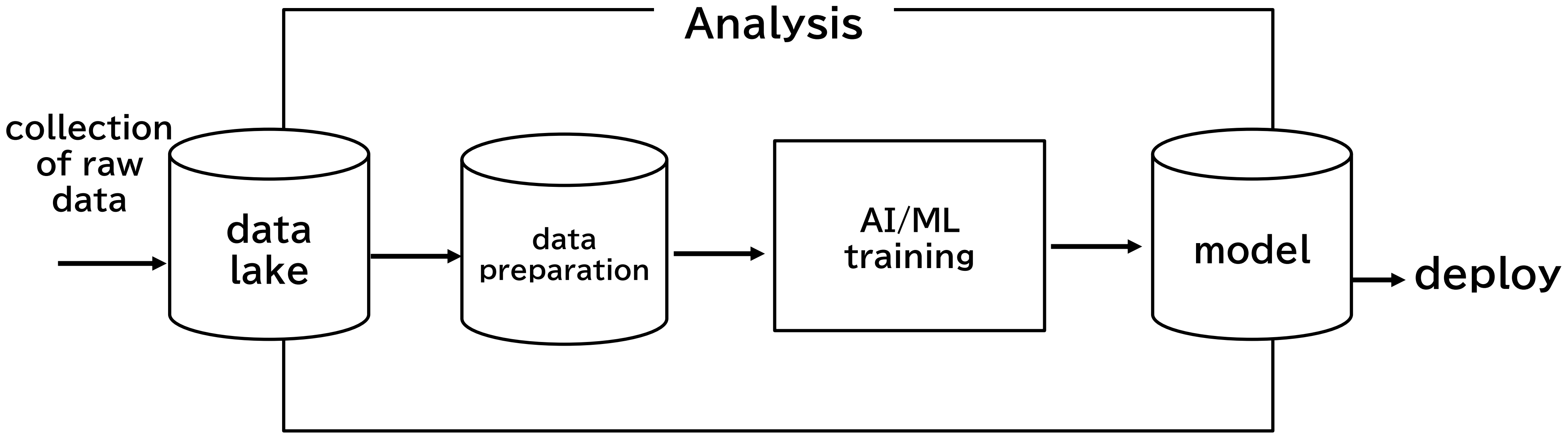


Workflow of a Data Scientist

almost 75% efforts of a Data Scientist spent on data preparation

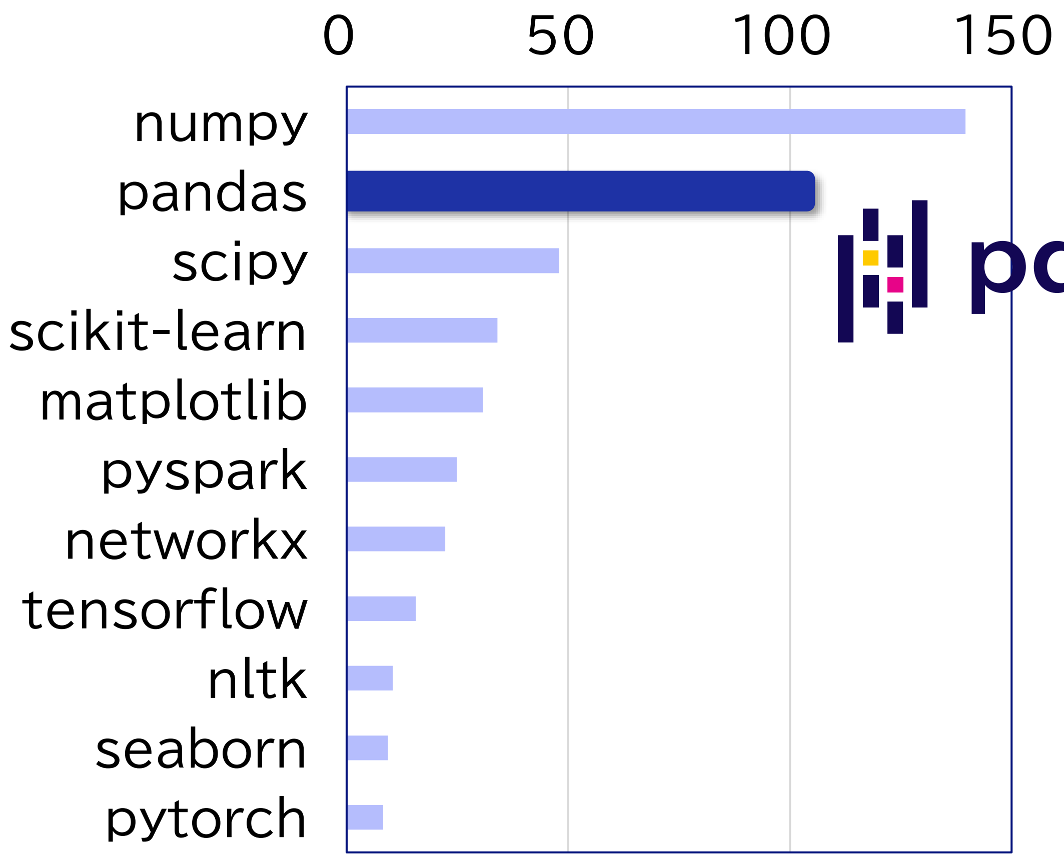


Anaconda:
The State of Data Science 2020



Pandas: Its Pros and Cons

◆ **Most popular Python library for data analytics.**



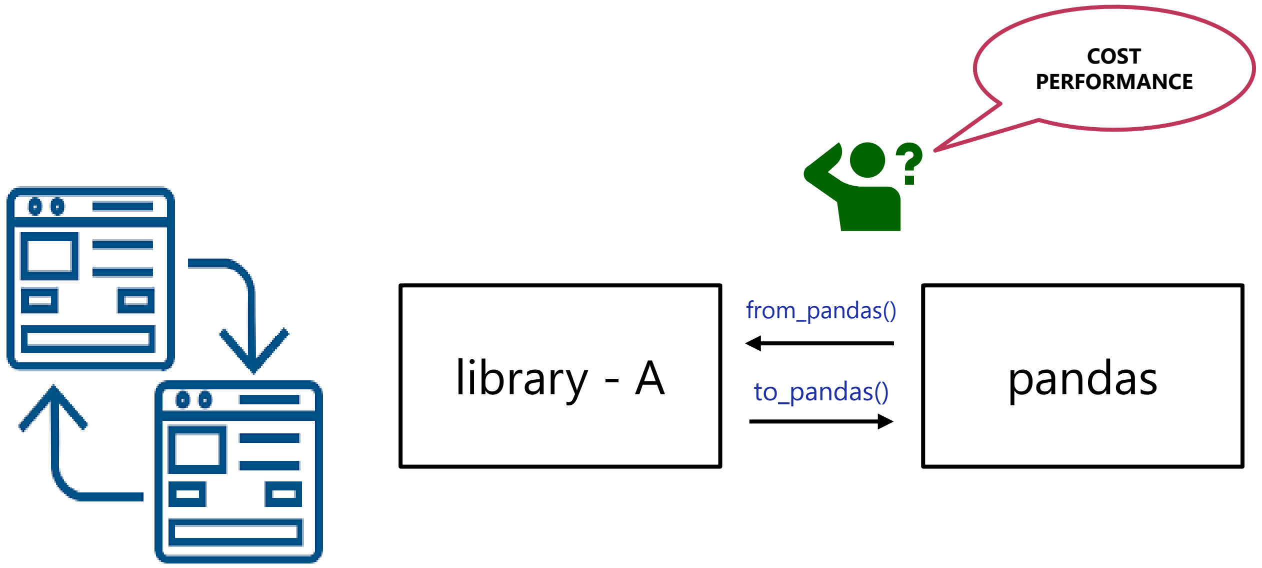
Monthly download from pypi.org
(Data Analytics Libraries)

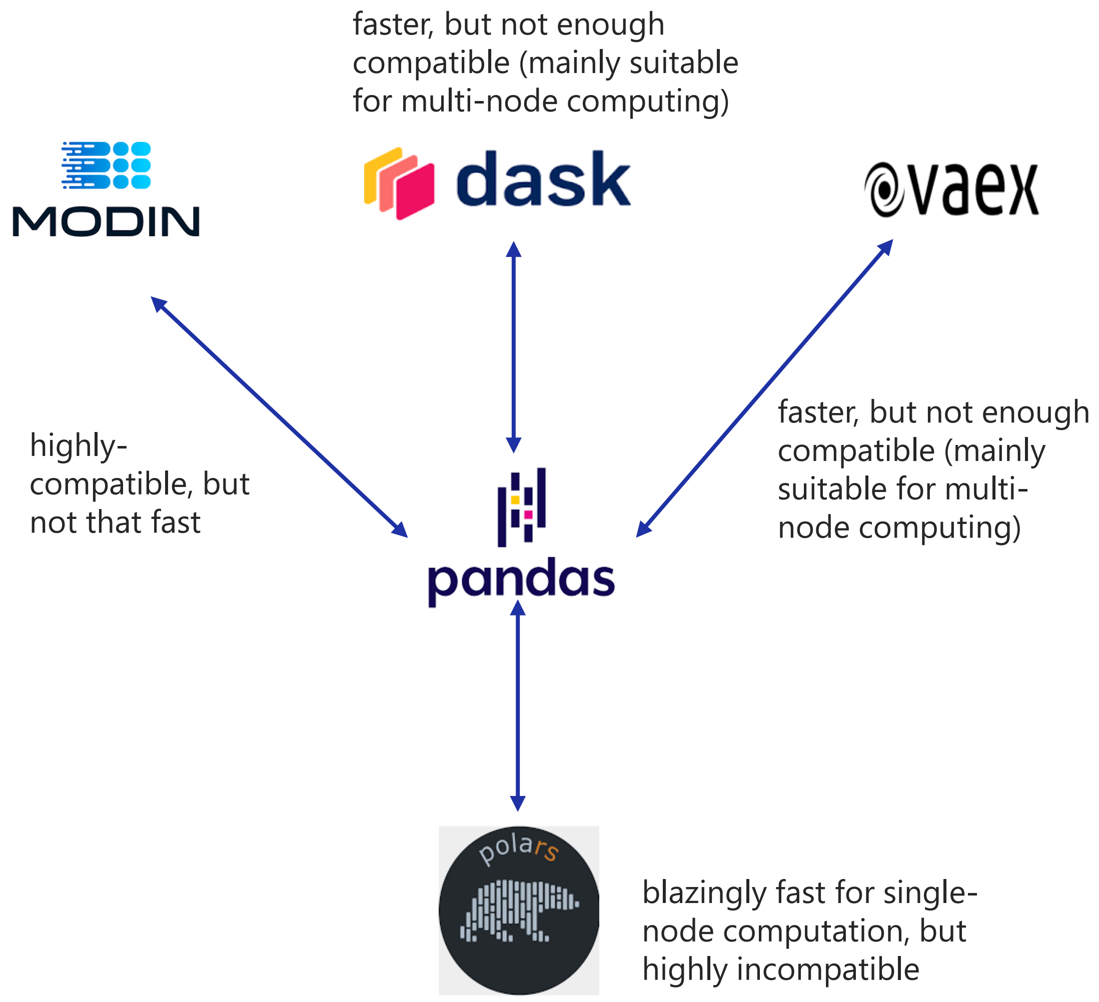
- It (mostly) doesn't support parallel computation.
- It doesn't have any auto-optimization feature.
- The choice of API heavily impacts the performance of a pandas application.
- Very slow execution reduces the efficiency of a data analyst.
- Long-running execution
  - produces higher cloud costs
  - attributes to higher CO2 emission

Challenges in Migration from pandas

Three most common challenges in switching from pandas:

- Needs to learn new library and their interfaces.
- Manual fallback to pandas when the target library doesn’t support a method used in an existing pandas application.
- Performance can be evaluated, and results can be tested after the migration is completed.




faster, but not enough compatible (mainly suitable for multi-node computing)
MODIN
dask
vaex
highly-compatible, but not that fast
pandas
faster, but not enough compatible (mainly suitable for multi-node computing)
polars
blazingly fast for single-node computation, but highly incompatible

Introducing FireDucks

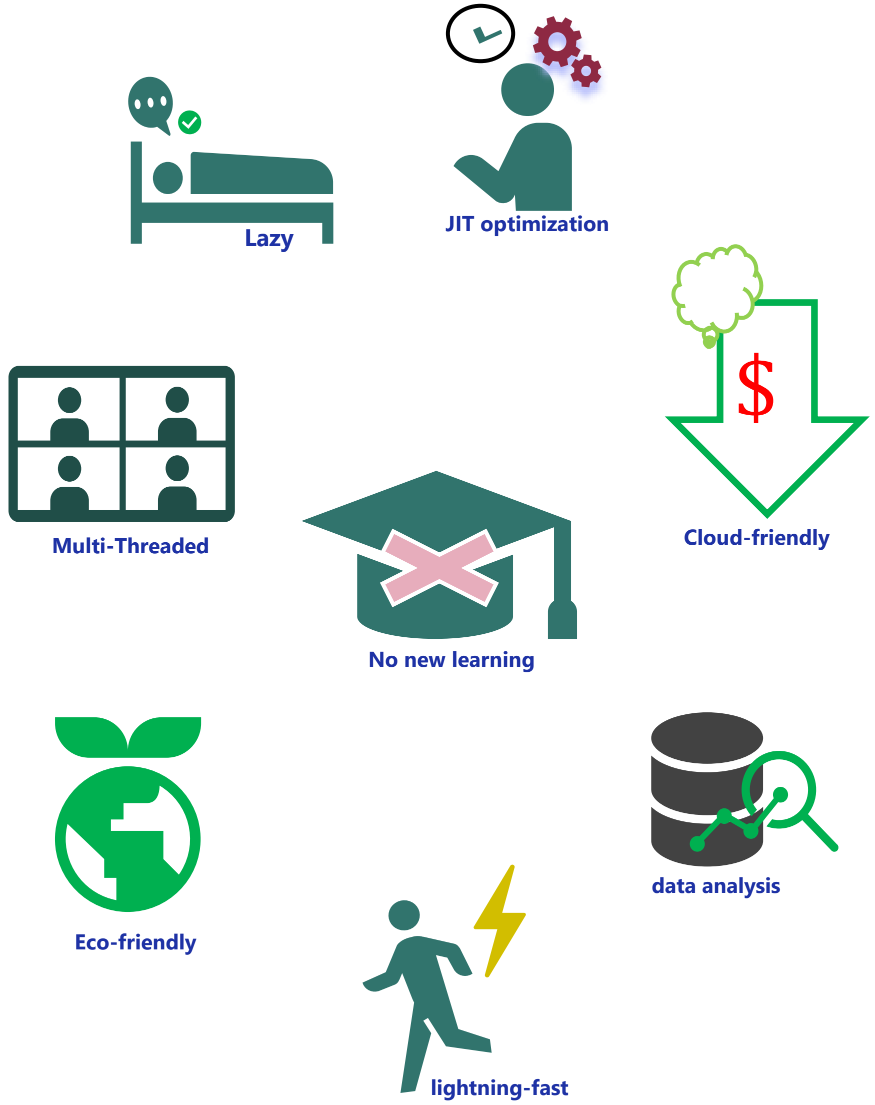
FireDucks (**F**lexible **IR E**ngine for DataFrame) is a high-performance compiler-accelerated DataFrame library with highly compatible pandas APIs.

Speed: significantly faster than pandas

- FireDucks is multithreaded to fully exploit the modern processor
- Lazy execution model with Just-In-Time optimization using a defined-by-run mechanism supported by MLIR (a subproject of LLVM).
  - supports both lazy and non-lazy execution models without modifying user programs (same API).

Ease of use: drop-in replacement of pandas

- FireDucks is highly compatible with pandas API
  - seamless integration is possible not only for an existing pandas program but also for any external libraries (like seaborn, scikit-learn, etc.) that internally use pandas dataframes.
- No extra learning is required
- No code modification is required



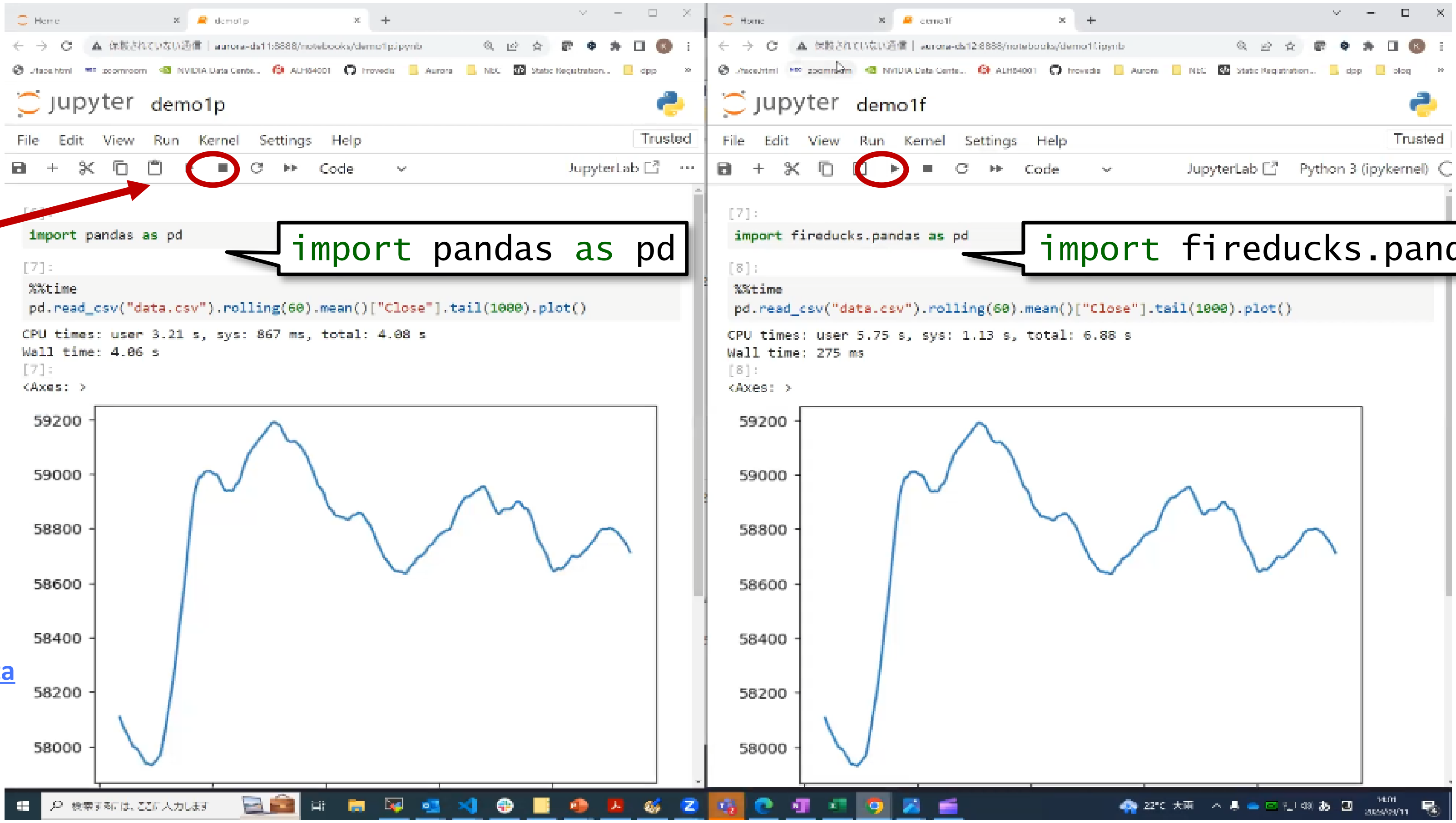
Let’s Have a Quick Demo!

```
pd.read_csv(“data.csv”).rolling(60).mean()[“Close”].tail(1000).plot()
```

Program to calculate moving average

pandas the difference is only in the import **FireDucks**

button to start execution



```
import pandas as pd
[7]:
%%time
pd.read_csv("data.csv").rolling(60).mean()["Close"].tail(1000).plot()
CPU times: user 3.21 s, sys: 867 ms, total: 4.08 s
Wall time: 4.06 s
[7]:
<Axes: >
```

```
[7]:
import fireducks.pandas as pd
[8]:
%%time
pd.read_csv("data.csv").rolling(60).mean()["Close"].tail(1000).plot()
CPU times: user 5.75 s, sys: 1.13 s, total: 6.88 s
Wall time: 275 ms
[8]:
<Axes: >
```

```
import pandas as pd
```

```
import fireducks.pandas as pd
```

pandas: 4.06s

~15x

FireDucks: 275ms

data.csv:
Bitcoin Historical Data

\Orchestrating a brighter world NEC

Usage of FireDucks

1. Explicit Import

easy to import

```
# import pandas as pd
import fireducks.pandas as pd
```

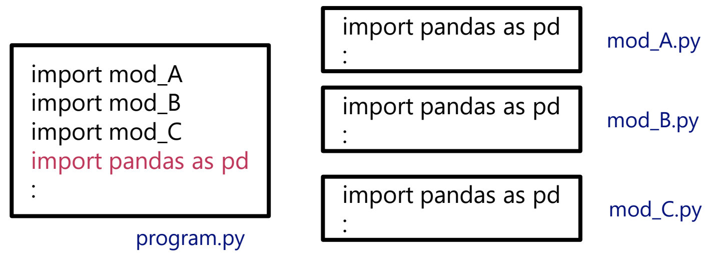
simply change the import statement

2. Import Hook

FireDucks provides command line option to automatically replace "**pandas**" with "**fireducks.pandas**"

```
$ python -m fireducks.pandas program.py
```

zero code modification



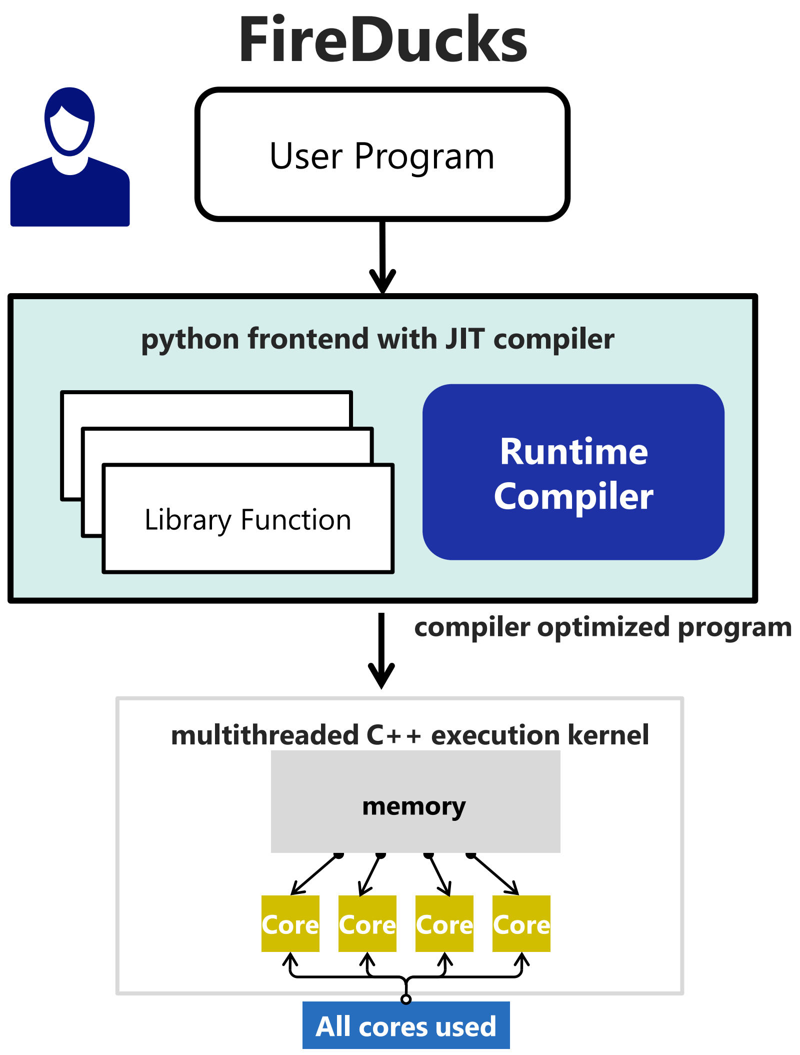
3. Notebook Extension

FireDucks provides simple import extension for interative notebooks.

```
%load_ext fireducks.pandas
import pandas as pd
```

simple integration in a notebook

Optimization Features



FireDucks
User Program
python frontend with JIT compiler
Library Function
Runtime Compiler
compiler optimized program
multithreaded C++ execution kernel
memory
Core
Core
Core
Core
All cores used

1. **Compiler Specific Optimizations**: Common Sub-expression Elimination, Dead-code Elimination, Constant Folding etc.
2. **Domain Specific Optimization**: Optimization at query-level: reordering instructions etc.
3. **Pandas Specific Optimization**: selection of suitable pandas APIs, selection of suitable parameter etc.

1. **Multi-threaded Computation**: Leverage all the available computational cores.
2. **Efficient Memory Management**: Data Structures backed by Apache Arrow
3. **Optimized Kernels**: Patented algorithms for Database like kernel operations: like sorting, join, filter, groupby, dropna etc. developed in C++ from scratch.

Compiler Specific Optimizations

- **Common mistakes often found in Kaggle notebooks**
  - same operation on the same data repeatedly
  - computation without further usage

The in-built compiler of FireDucks can auto-detect such issues and optimize at runtime.

```
# Find year and month-wise average sales
df[“year”] = pd.to_datetime(df[“time”]).dt.year
df[“month”] = pd.to_datetime(df[“time”]).dt.month
r = df.groupby([“year”, “month”])[“sales”].mean()
```

⇩ **C**ommon **S**ub-expression **E**limination

```
s = pd.to_datetime(df[“time”])
df[“year”] = s.dt.year
df[“month”] = s.dt.month
r = df.groupby([“year”, “month”])[“sales”].mean()
```

```
def func(x: pd.DataFrame, y: pd.DataFrame):
   merged = x.merge(y, on="key")
   sorted = merged.sort_values(by="key")
   return merged.groupby("key").max()
```

⇩ **D**ead **C**ode **E**limination

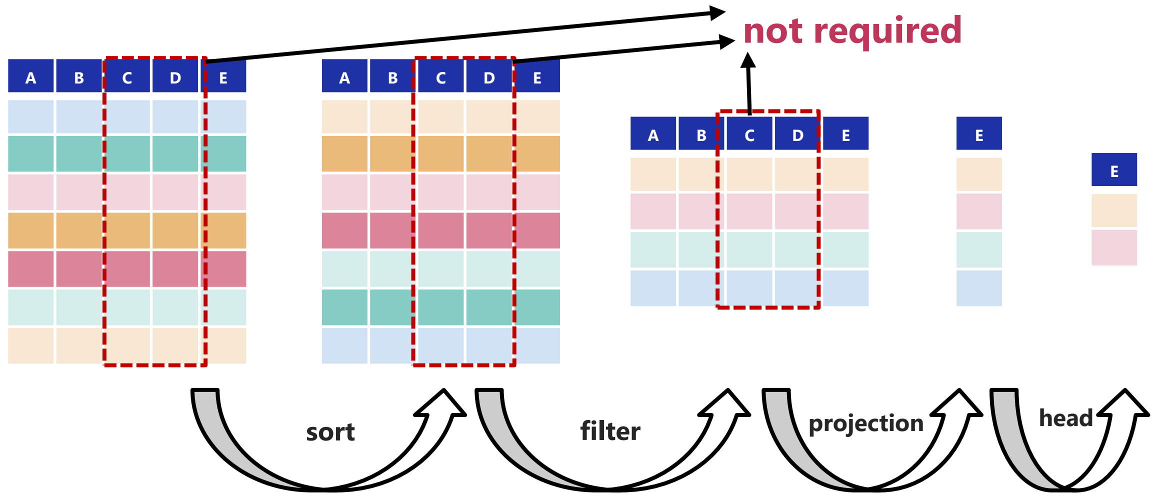
```
def func(x: pd.DataFrame, y: pd.DataFrame):
   merged = x.merge(y, on="key")
   return merged.groupby("key").max()
```

[Have you ever thought of speeding up your data analysis in pandas with a compiler?]()

Execution order matters to boost the performance of a data analysis tool

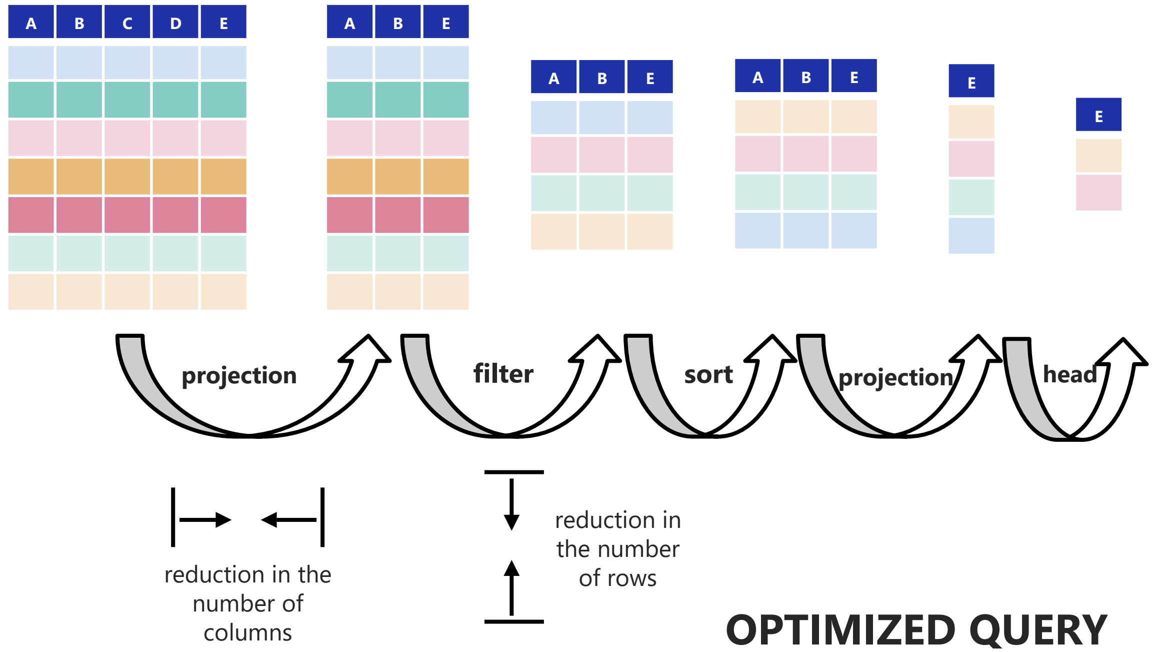
```
df.sort_values("A")
  .query("B > 1")["E"]
  .head(2)
```

※sort-order: yellow->red->green->blue



SAMPLE QUERY

```
df.loc[:, ["A", "B", "E"]]
  .query("B > 1")
  .sort_values("A")["E"]
  .head(2)
```



A
B
C
D
E
projection
filter
sort
projection
head
reduction in the number of columns
reduction in the number of rows

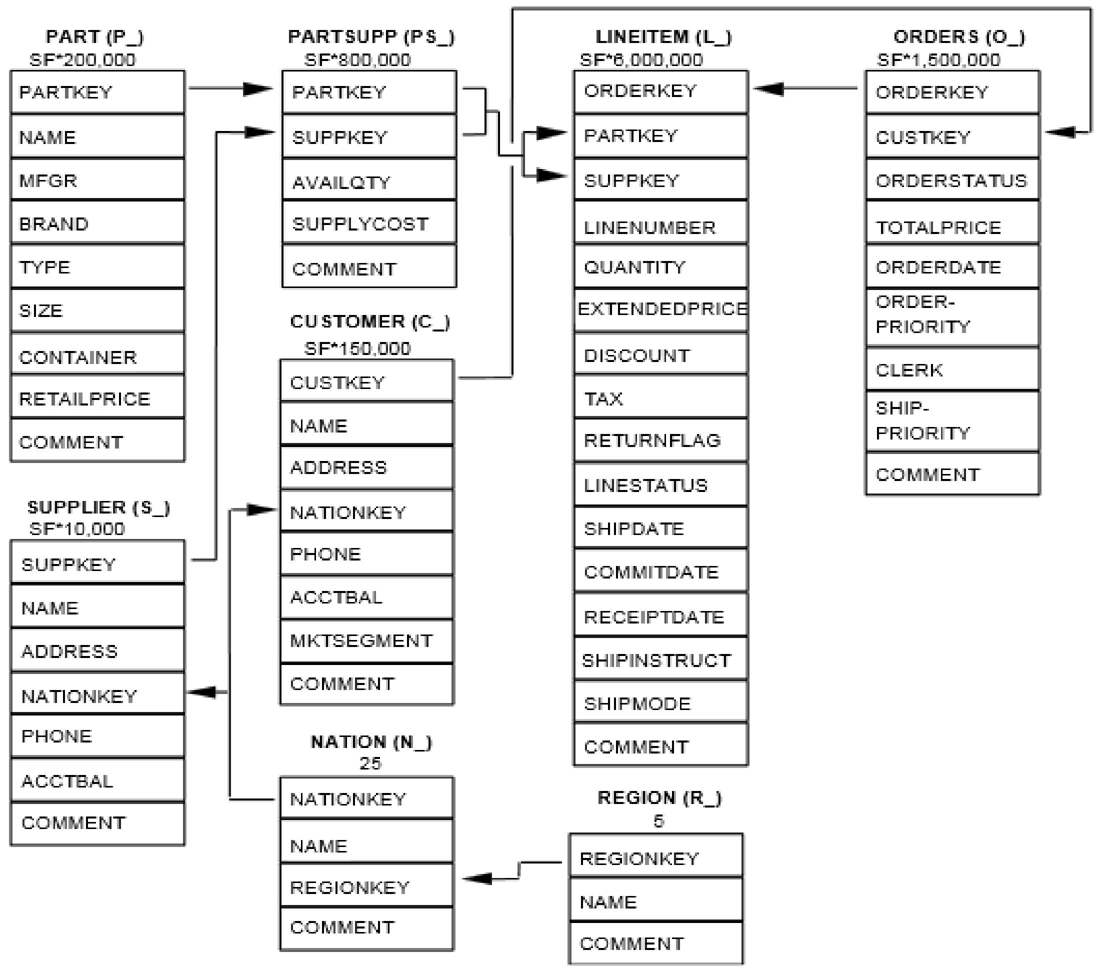
OPTIMIZED QUERY

Exercise: Query #3 from TPC-H Benchmark (SQL -> pandas)

◆ query to retrieve the 10 unshipped orders with the highest value.

```
SELECT l_orderkey,
               sum(l_extendedprice * (1 - l_discount)) as revenue,
               o_orderdate,
               o_shippriority
FROM customer, orders, lineitem
WHERE
    c_mktsegment = 'BUILDING' AND
    c_custkey = o_custkey AND
    l_orderkey = o_orderkey AND
    o_orderdate < date '1995-03-15' AND
    l_shipdate > date '1995-03-15′
GROUP BY l_orderkey, o_orderdate, o_shippriority
ORDER BY revenue desc, o_orderdate
LIMIT 10;
```

```
rescols = ["l_orderkey", “revenue”, "o_orderdate", "o_shippriority“]
result = (
 customer.merge(orders, left_on="c_custkey", right_on="o_custkey")
  .merge(lineitem, left_on="o_orderkey", right_on="l_orderkey")
  .pipe(lambda df: df[df[“c_mktsegment"] == "BUILDING"])
  .pipe(lambda df: df[df["o_orderdate"] < datetime(1995, 3, 15)])
  .pipe(lambda df: df[df["l_shipdate"] > datetime(1995, 3, 15)])
  .assign(revenue=lambda df: df["l_extendedprice"] * (1 - df["l_discount"]))
  .groupby(["l_orderkey", "o_orderdate", "o_shippriority"], as_index=False)
  .agg({"revenue": "sum”})[rescols]
  .sort_values(["revenue", "o_orderdate"], ascending=[False, True])
  .head(10)
)
```

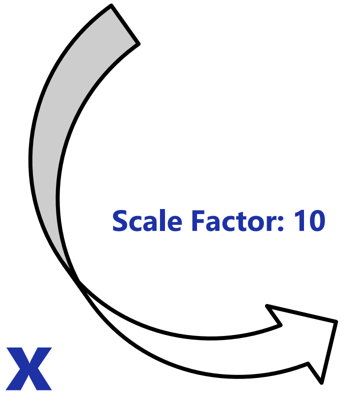


Exercise: Query #3 from TPC-H Benchmark (pandas -> optimized pandas)

```
rescols = ["l_orderkey", “revenue”, "o_orderdate", "o_shippriority“]
result = (
 customer.merge(orders, left_on="c_custkey", right_on="o_custkey")
  .merge(lineitem, left_on="o_orderkey", right_on="l_orderkey")
  .pipe(lambda df: df[df[“c_mktsegment"] == "BUILDING"])
  .pipe(lambda df: df[df["o_orderdate"] < datetime(1995, 3, 15)])
  .pipe(lambda df: df[df["l_shipdate"] > datetime(1995, 3, 15)])
  .assign(revenue=lambda df: df["l_extendedprice"] * (1 - df["l_discount"]))
  .groupby(["l_orderkey", "o_orderdate", "o_shippriority"], as_index=False)
  .agg({"revenue": "sum”})[rescols]
  .sort_values(["revenue", "o_orderdate"], ascending=[False, True])
  .head(10)
)
```

Such domain specific optimizations can be performed by FireDucks automatically

Exec-time: 68.55 s



Scale Factor: 10

6.5x

Exec-time: 10.33 s

```
# projection-filter: to reduce scope of “customer” table to be processed
cust = customer[[“c_custkey”, “c_mktsegment"]]
f_cust = cust[cust[“c_mktsegment"] == "BUILDING"]

# projection-filter: to reduce scope of “orders” table to be processed
ord = orders[[“o_custkey”, “o_orderkey”, “o_orderdate”, "o_shippriority"]]
f_ord = ord[ord["o_orderdate"] < datetime(1995, 3, 15)]

# projection-filter: to reduce scope of “lineitem” table to be processed
litem = lineitem[["l_orderkey“, "l_shipdate“, "l_extendedprice“, "l_discount"]]
f_litem = litem[litem["l_shipdate"] > datetime(1995, 3, 15)]

rescols = ["l_orderkey", “revenue”, "o_orderdate", "o_shippriority“]
result = ( f_cust.merge(f_ord, left_on="c_custkey", right_on="o_custkey")
  .merge(f_litem, left_on="o_orderkey", right_on="l_orderkey")
  .assign(revenue=lambda df: df["l_extendedprice"] * (1 - df["l_discount"]))
  .pipe(lambda df: df[rescols])
  .groupby(["l_orderkey", "o_orderdate", "o_shippriority"], as_index=False)
  .agg({"revenue": "sum"})[rescols]
  .sort_values(["revenue", "o_orderdate"], ascending=[False, True])
  .head(10)
)
```

Pandas Specific Optimization – Parameter Tuning

parameter tuning in pandas

# department-wise average salaries sorted in descending order

groupby("department", sort=True)

```
res = (
   employee.groupby("department")["salary"]
                .mean()
                .sort_values(ascending=False)
)
```

```
res = (
   employee.groupby("department", sort=False)["salary"]
                .mean()
                .sort_values(ascending=False)
)
```

department	salary (USD)
IT	85,000
Admin	60,000
Finance	100,000
IT	81,000
Finance	95,000
Corporate	78,000
Sales	80,000

employee table

department	salary (USD)
IT	85,000
IT	81,000

department	salary (USD)
Admin	60,000

department	salary (USD)
Finance	100,000
Finance	95,000

department	salary (USD)
Corporate	78,000

department	salary (USD)
Sales	80,000

creating groups

department	salary (USD)
IT	83,000
Admin	60,000
Finance	97,500
Corporate	78,000
Sales	80,000

group-wise average-salary

department	salary (USD)
Admin	60,000
Corporate	78,000
Finance	97,500
IT	83,000
Sales	80,000

group-wise average-salary
sorted by "department"

department	salary (USD)
Finance	97,500
IT	83,000
Sales	80,000
Corporate	78,000
Admin	60,000

group-wise average-salary
sorted by "department"

```
df.groupby(["A", "B"])["C"]
  .mean()
  .sort_values(ascending=False)
```

~50 sec

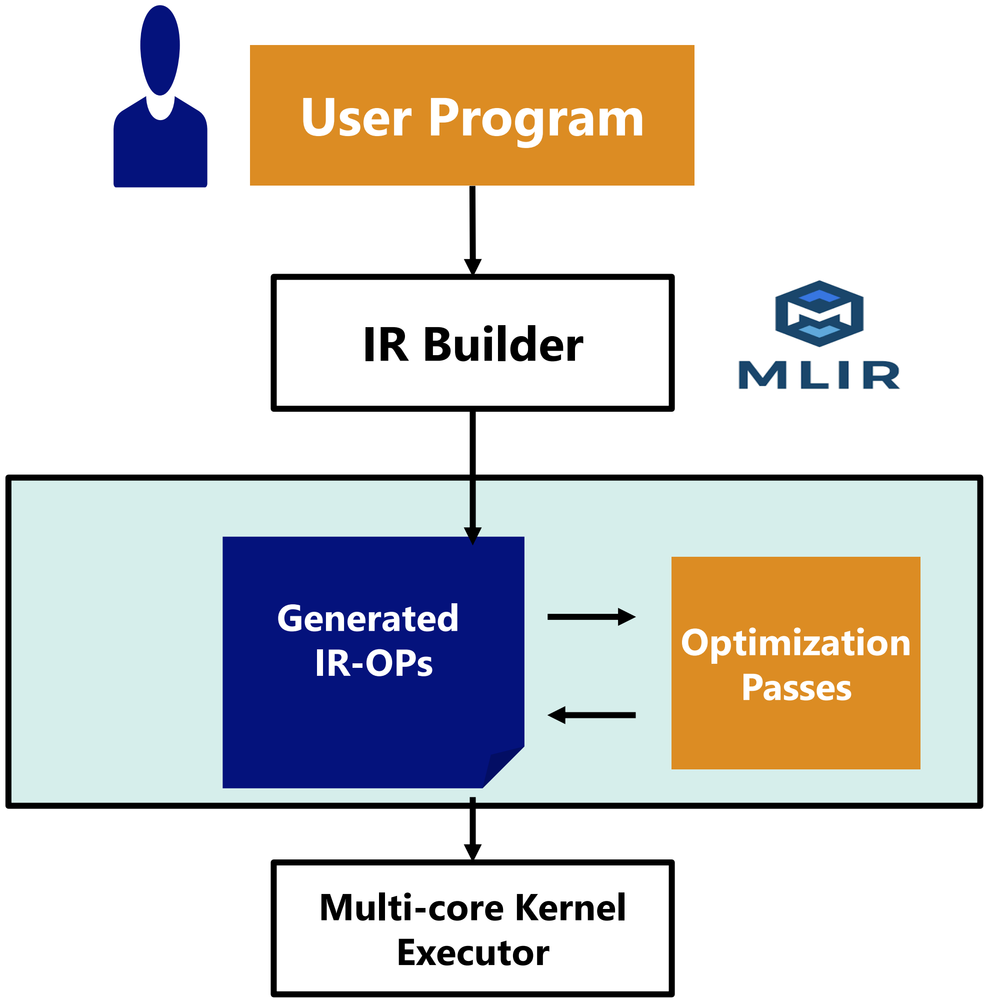
```
df.groupby(["A", "B"], sort=False)["C"]
  .mean()
  .sort_values(ascending=False)
```

~30 sec

100M samples with high-cardinality

How does FireDucks work?

※IR: Intermediate Representation



```
sorted = df.sort_values("b")
result = sorted["a"]
```

↓

```
%v2 = "fireducks.sort_values"(%v1,"b")
%v3 = "fireducks.project"(%v2,["a"])
```

↓ **print (result)**

```
%v11 = "fireducks.project"(%v1,["a","b"])
%v2 = "fireducks.sort_values"(%v11,"b")
%v3 = "fireducks.project"(%v2,["a"])
```

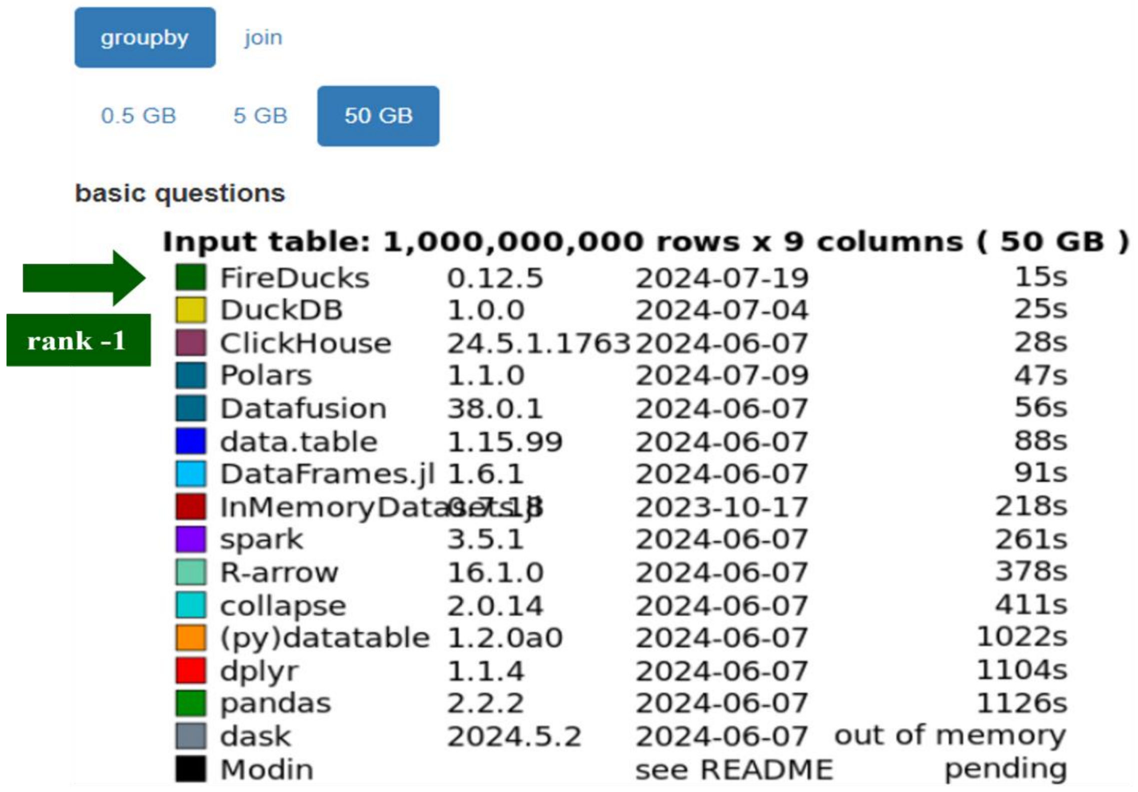
↓

```
tmp = df[["a","b"]]
sorted = tmp.sort_values("b")
result = sorted["a"]
```

Primary Objective: <u>Write Once, Execute Anywhere</u>

Benchmark (1): DB-Benchmark

Database-like ops benchmark (https://duckdblabs.github.io/db-benchmark)

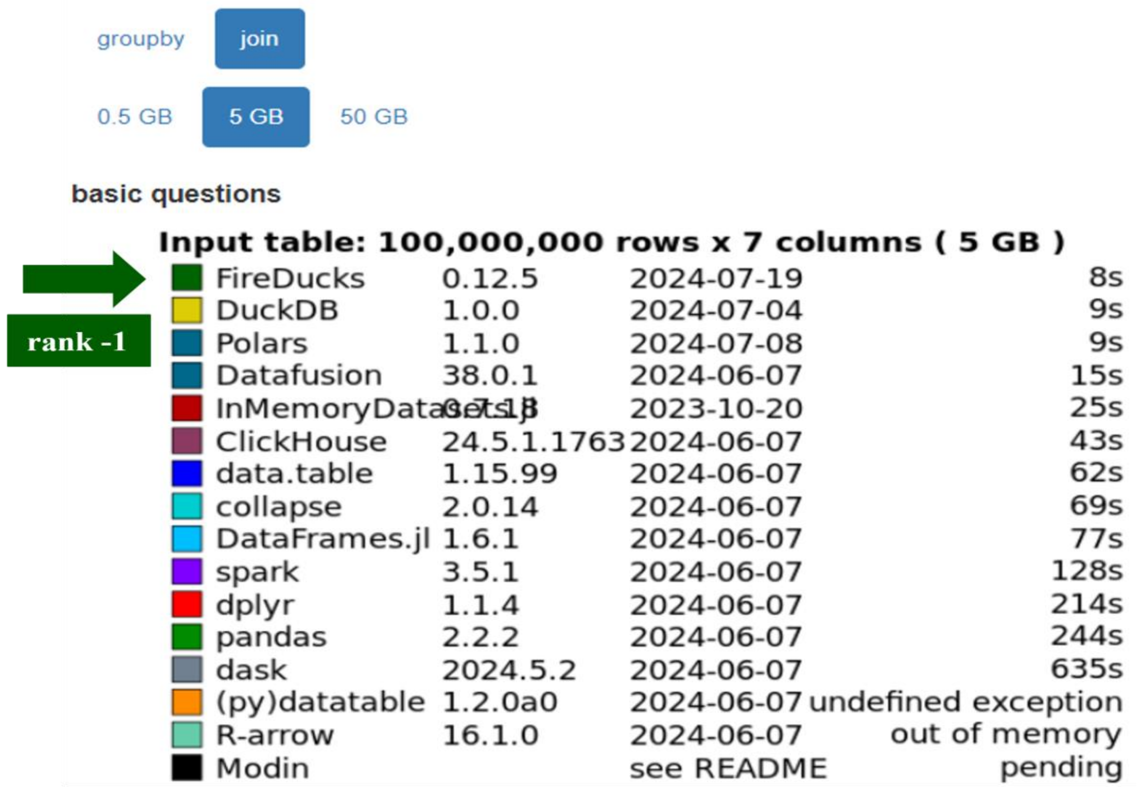


basic questions

Input table: 1,000,000,000 rows x 9 columns (50 GB)

🟩	FireDucks	0.12.5	2024-07-19	15s
🟨	DuckDB	1.0.0	2024-07-04	25s
🟪	ClickHouse	24.5.1.1763	2024-06-07	28s
🟦	Polars	1.1.0	2024-07-09	47s
🟦	Datafusion	38.0.1	2024-06-07	56s
🟦	data.table	1.15.99	2024-06-07	88s
🟦	DataFrames.jl	1.6.1	2024-06-07	91s
🟥	InMemoryDatasets	0.7.18	2023-10-17	218s
🟪	spark	3.5.1	2024-06-07	261s
🟩	R-arrow	16.1.0	2024-06-07	378s
🟦	collapse	2.0.14	2024-06-07	411s
🟧	(py)datatable	1.2.0a0	2024-06-07	1022s
🟥	dplyr	1.1.4	2024-06-07	1104s
🟩	pandas	2.2.2	2024-06-07	1126s
⬜	dask	2024.5.2	2024-06-07	out of memory
⬛	Modin		see README	pending

groupby



basic questions

Input table: 100,000,000 rows x 7 columns (5 GB)

🟩	FireDucks	0.12.5	2024-07-19	8s
🟨	DuckDB	1.0.0	2024-07-04	9s
🟦	Polars	1.1.0	2024-07-08	9s
🟦	Datafusion	38.0.1	2024-06-07	15s
🟥	InMemoryDatasets	0.7.18	2023-10-20	25s
🟪	ClickHouse	24.5.1.1763	2024-06-07	43s
🟦	data.table	1.15.99	2024-06-07	62s
🟦	collapse	2.0.14	2024-06-07	69s
🟦	DataFrames.jl	1.6.1	2024-06-07	77s
🟪	spark	3.5.1	2024-06-07	128s
🟥	dplyr	1.1.4	2024-06-07	214s
🟩	pandas	2.2.2	2024-06-07	244s
⬜	dask	2024.5.2	2024-06-07	635s
🟧	(py)datatable	1.2.0a0	2024-06-07	undefined exception
🟩	R-arrow	16.1.0	2024-06-07	out of memory
⬛	Modin		see README	pending

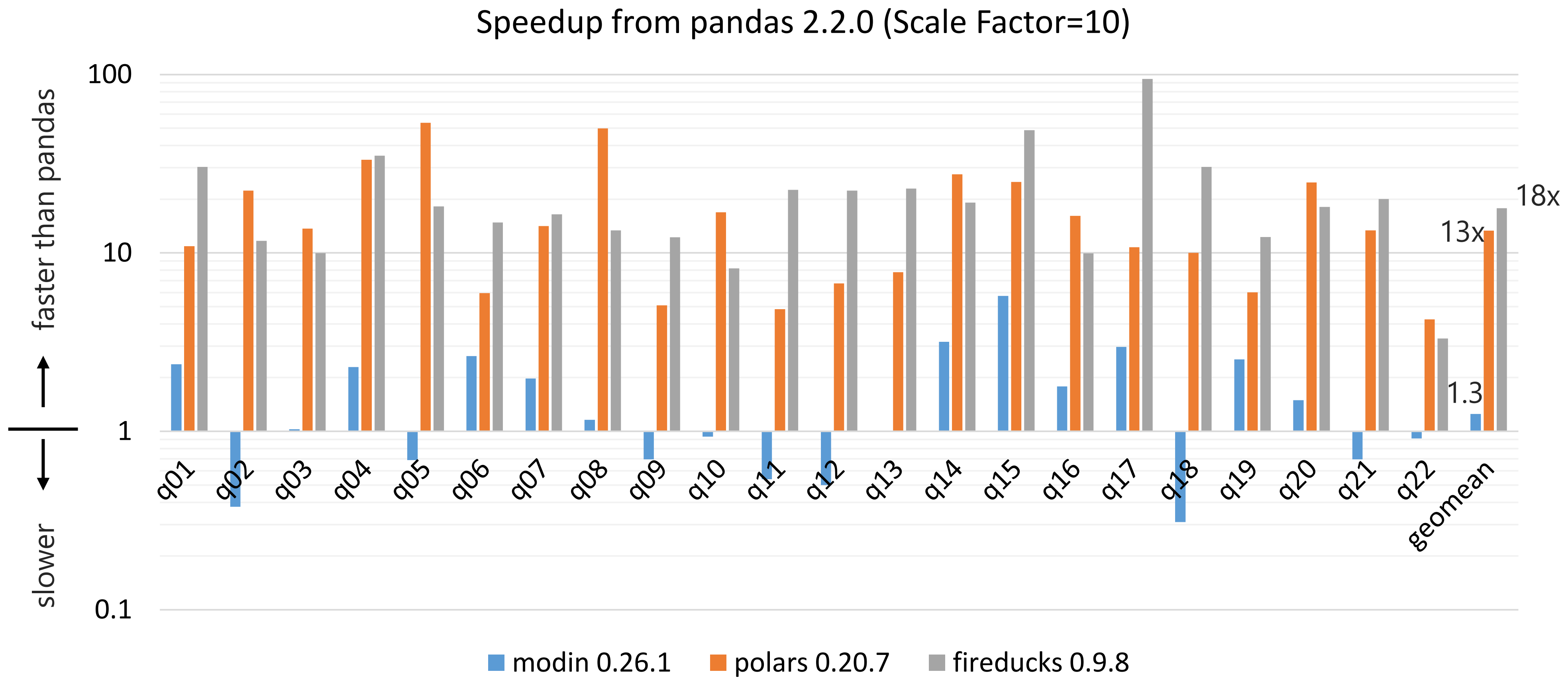
join

Benchmark (2): Speedup from pandas in TPC-H benchmark

FireDucks is 95x faster than pandas at max

Server

Xeon Gold 5317 x2
(24 cores), 256GB

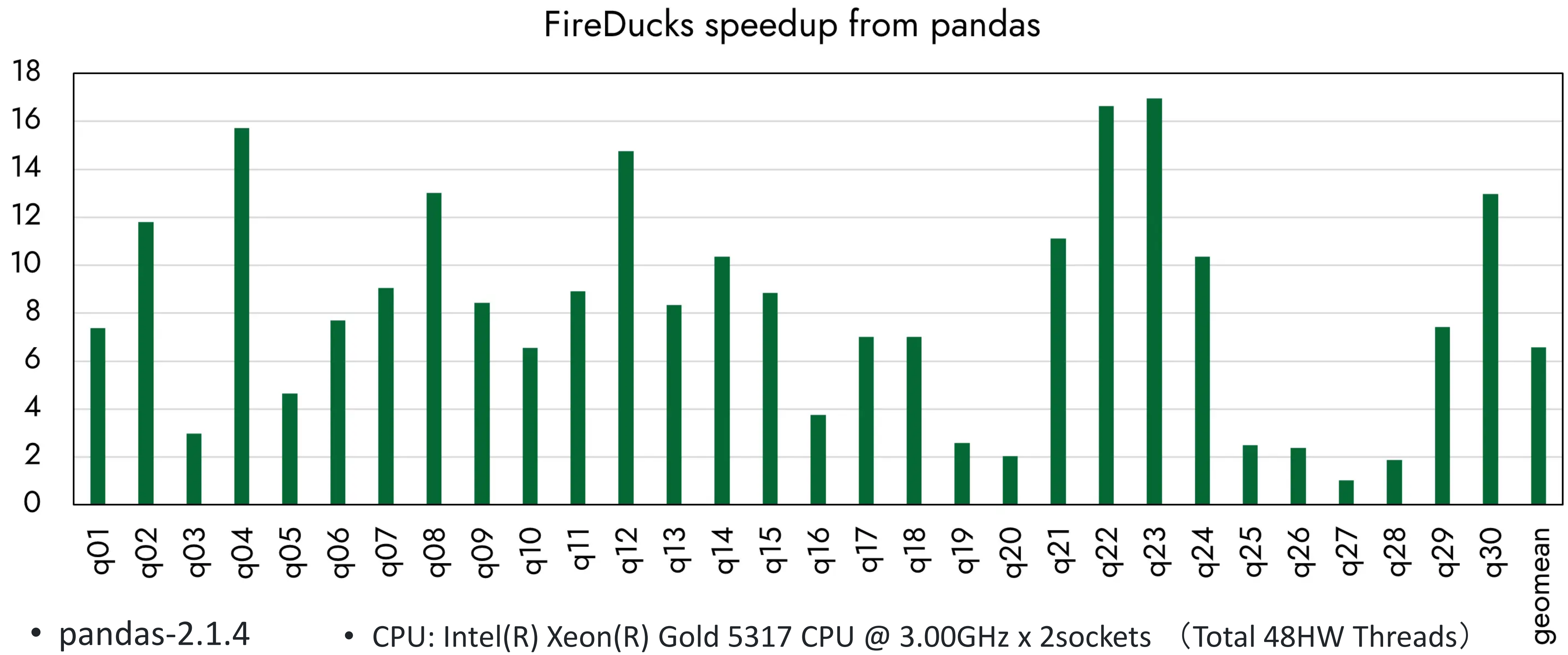


Comparison of DataFrame libraries (average speedup)

FireDucks	**18x**
Polars	13x
Modin	1.3x

Benchmark (3): Speedup from pandas in TPCx-BB benchmark

ETL(Extract, Transform, Load) and ML Workflow



- pandas-2.1.4
- fireducks-0.9.3

- CPU: Intel(R) Xeon(R) Gold 5317 CPU @ 3.00GHz x 2sockets （Total 48HW Threads）
- Main memory: 256GB

Resource on FireDucks

Web site (User guide, benchmark, blog)

https://fireducks-dev.github.io/

X(twitter) (Release information)

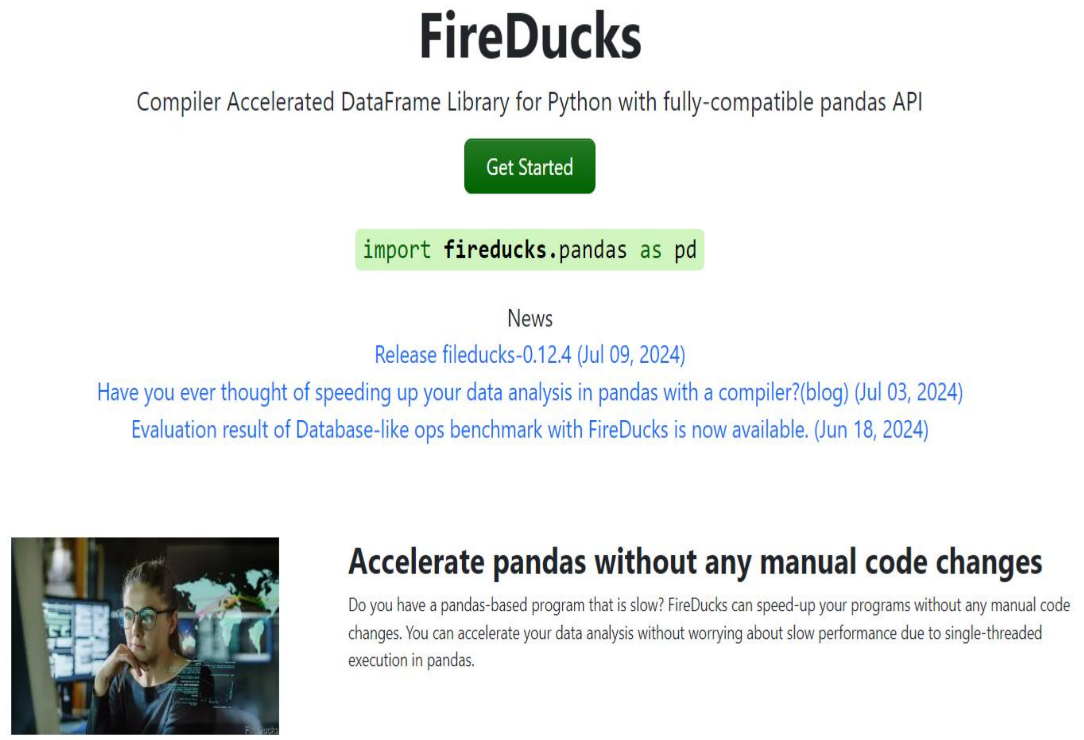
https://x.com/fireducksdev

Github (Issue report)

https://github.com/fireducks-dev/fireducks

slack **Q/A, communication**

https://join.slack.com/t/fireducks/shared_invite/zt-2j4lucmtj-IGR7AWlXO62Lu605pnBJ2w



FireDucks

Compiler Accelerated DataFrame Library for Python with fully-compatible pandas API

Get Started

```
import fireducks.pandas as pd
```

News

Release fileducks-0.12.4 (Jul 09, 2024)

Have you ever thought of speeding up your data analysis in pandas with a compiler?(blog) (Jul 03, 2024)

Evaluation result of Database-like ops benchmark with FireDucks is now available. (Jun 18, 2024)

Accelerate pandas without any manual code changes

Do you have a pandas-based program that is slow? FireDucks can speed-up your programs without any manual code changes. You can accelerate your data analysis without worrying about slow performance due to single-threaded execution in pandas.

Let’s go for a test drive!

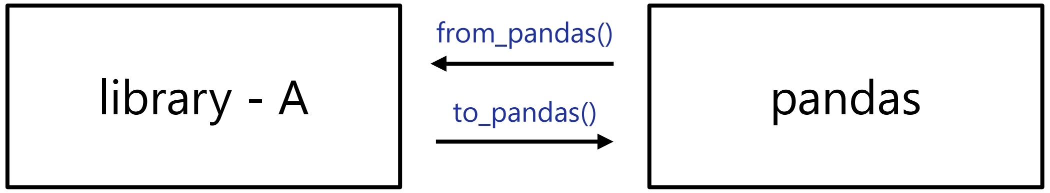
https://colab.research.google.com/drive/1qpej-X7CZsIeOqKuhBg4kq-cbGuJf1Zp?usp=sharing

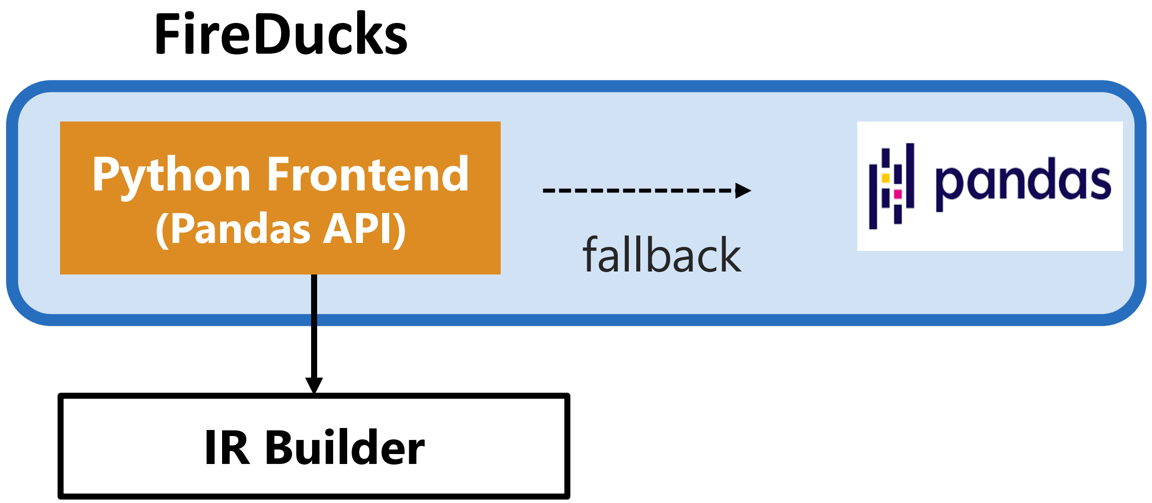
Thank You!

- Focus more on in-depth data exploration using “**pandas**”.
- Let the “**FireDucks**” take care of the optimization for you.
- Enjoy Green Computing!

Frequently Asked Questions

FAQ: Why FireDucks is highly compatible with pandas?





```
%load_ext fireducks.pandas    ← notebook extension for importhook
import pandas as pd
import numpy as np
```

```
%%fireducks.profile           ← notebook specific profiler
df = pd.DataFrame({
    "id": np.random.choice(list("abcdef"), 10000),
    "val": np.random.choice(100, 10000)
})

r1 =(
    df.sort_values("id")
       .groupby("id")
       .head(2)
       .reset_index(drop=True)
)
                pd.from_pandas(r1["val"].to_pandas().cumsum())
r1["val"] = r1["val"].cumsum()
r1.describe()
```

profiling-summary:: total: 42.4832 msec (fallback: 1.1448 msec)

	name	type	n_calls	duration (msec)
0	groupby_head	kernel	1	16.696805
1	sort_values	kernel	1	16.684564
2	from_pandas.frame.metadata	kernel	2	3.641694
3	to_pandas.frame.metadata	kernel	2	2.237987
4	describe	kernel	1	2.021135
5	DataFrame._repr_html_	fallback	1	1.021662
6	Series.cumsum	fallback	1	0.111802
7	setitem	kernel	1	0.010280
8	get_metadata	kernel	1	0.009650
9	reset_index	kernel	1	0.008050

When running a python script/program, you may like to set the environment variable to get fallback warning logs:
FIREDUCKS_FLAGS="-Wfallback"

Raise feature request when you encounter some expensive fallback hindering your program performance!

Directly **communicate** with us over our slack channel for any performance or API related queries!

FAQ: How to evaluate Lazy Execution?

```
def foo(employee, country):
   stime = time.time()
   m = employee.merge(country, on=“C_Code”)
   r = m[m[“Gender”] == “Male”]
   print(f”fireducks time: {time.time() – stime} sec”)
   return r
```

fireducks time: 0.0000123 sec

IR Builder

create_data_op(…)
merge_op(…)
filter_op(…)

```
def foo(employee, country):
   employee._evaluate()
   country._evaluate()
   stime = time.time()
   m = employee.merge(country, on=“C_Code”)
   r = m[m[“Gender”] == “Male”]
   r._evaluate()
   print(f”fireducks time: {time.time() – stime} sec”)
   return r
```

fireducks time: 0.02372143 sec

FIREDUCKS_FLAGS="--benchmark-mode”

Use this to disable lazy-execution mode when you do not want to make any changes in your existing application during performance evaluation.

FAQ: How to configure number of cores to be used?

OMP_NUM_THREADS=1

Use this to stop parallel execution, or configure this with the intended number of cores to be used

Alternatively, you can use the Linux taskset command to bind your program with specific CPU cores.

\Orchestrating a brighter world

NEC creates the social values of safety, security,
fairness and efficiency to promote a more sustainable world
where everyone has the chance to reach their full potential.

\Orchestrating a brighter world

NEC