

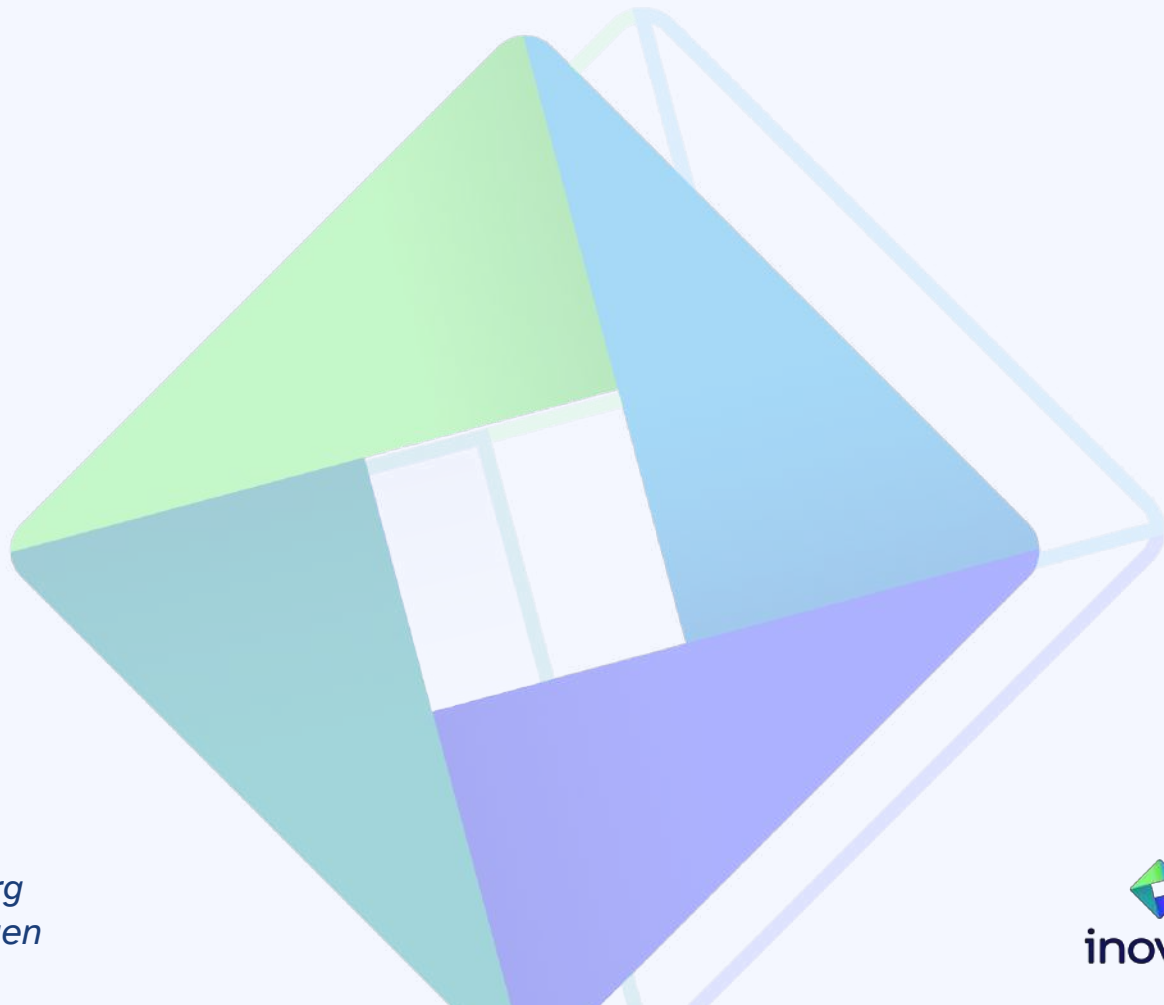
# Polars



DataFrames for the new era

**Team inovex**

*Karlsruhe · Köln · München · Hamburg  
Berlin · Stuttgart · Pforzheim · Erlangen*



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7. & 8. June 2024 in Munich



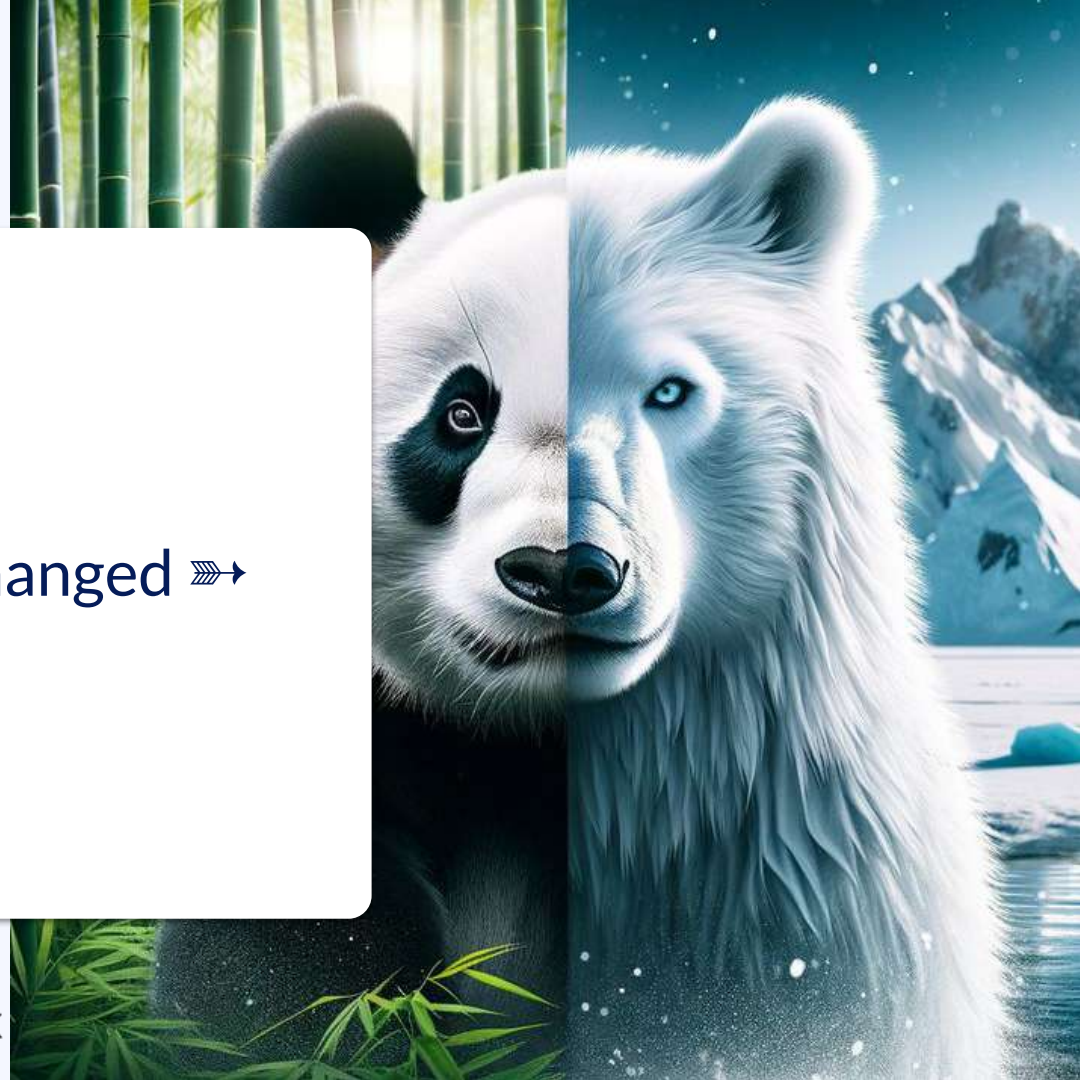
<https://app.inovex.ai>



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# Agenda

- How it has been 🐼
- How the landscape changed ➡
- Polars 🐻



# Pandas

Everyone's favorite DataFrame Library



# Pandas






- Python DataFrame for data manipulation and analysis
- Built upon NumPy
- Open Source (BSD License)
- Created in 2008
- Downloaded 191\_780\_336 last month<sup>1</sup>





# Pandas



## Pros

-  Everyone knows it
-  Integrated into everything  
(Plotting, DBs, ...)
-  Large and active community  
support (docs, tutorials, ...)

## Cons

-  Inconsistent API
-  Performance Issues
-  No multi-core processing
-  No zero-copy sharing

# How the landscape changed

A new era?



## How the landscape changed

- Explosion in data volume and complexity
- Increased diversity of data processing frameworks
- Emphasis on leveraging multi-core CPU architectures
- Transition to in-memory computing for real-time insights
- Growth of machine learning and AI applications





# Apache Arrow

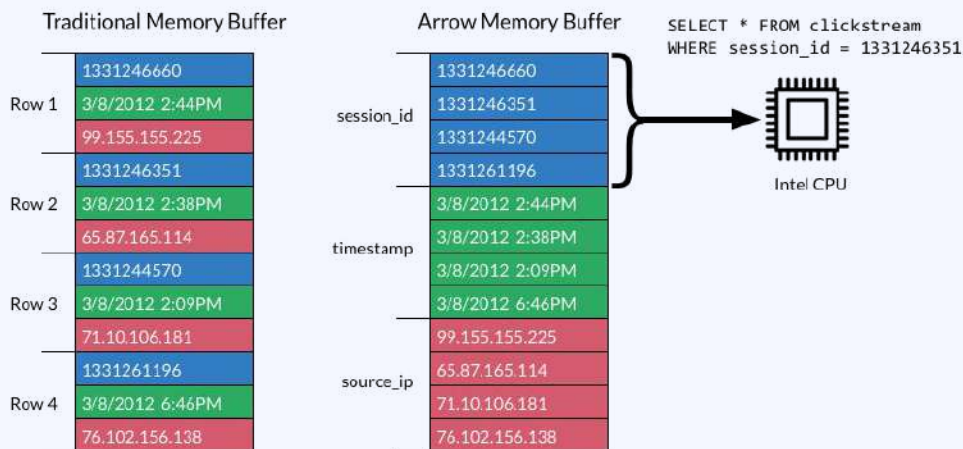


1. Language-independent columnar memory format for data
2. Designed for efficient analytics on CPUs/GPUs
3. Supports zero-copy reads, eliminating serialization overhead
4. Wide library support across multiple programming languages
5. Community-driven development with open consensus decision-making

# Apache Arrow Format



	session_id	timestamp	source_ip
Row 1	1331246660	3/8/2012 2:44PM	99.155.155.225
Row 2	1331246351	3/8/2012 2:38PM	65.87.165.114
Row 3	1331244570	3/8/2012 2:09PM	71.10.106.181
Row 4	1331261196	3/8/2012 6:46PM	76.102.156.138



# German Style Strings (Hyper/Umbra)



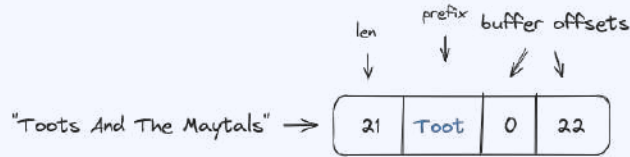
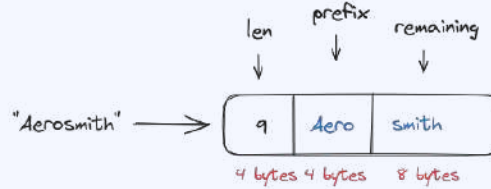
Previously:

data: Buffer<u8>

ABBAThe Velvet UndergroundToots And The MayTals

offsets: Buffer<i64>

0,4,26,47



The Velvet UndergroundToots And The MayTals

## Projects Powered by Apache Arrow

APACHE

ARROW



[tile]DB



ClickHouse



RAY



*influxdb*



# Polars








DataFrames for the new era



# Polars - A Modern DataFrame Library



-  **Fast, Multi-threaded Query Engine:** Written in Rust for effective parallelism
-  **Vectorized, Columnar Processing:** Enables high performance on modern processors
-  **Intuitive Data Wrangling:** Expressions familiar to data scientists and analysts
-  **Readable and Performant Code:** Balance between clarity and efficiency
-  **Committed to Open Source:** Active community contributions under MIT license

# Project Overview



- Created by [Ritchie Vink](#)
- License: [MIT](#)
- [Github](#): 25k ★
- Bindings (mthly DLs): [Rust](#) (75k), [Python](#) (3.5M), [JavaScript](#) (20k), R

Contributions to main, excluding merge commits



Source: <https://github.com/pola-rs/polars/graphs/contributors>



## Supports all common data formats

- **Text:** CSV & JSON
- **Binary:** Parquet, Delta Lake, AVRO & Excel
- **IPC:** Feather, Arrow
- **Databases:**
  - **read:** SQLAlchemy, connector-x & ADBC
  - **write:** SQLAlchemy, Arrow Database Connectivity (ADBC)
- **S3 Cloud storage:** AWS, Azure, GCP
- **Google Big Query**
- **Apache Iceberg tables**





# Dataset: eCommerce behavior data from multi category store

- [Kaggle Dataset](#), data collected by [Open CDP](#) project
- **Nov 2019**: 67,501,979 rows (CSV 8.4GB , Parquet: 2GB)
- Each row represents an event
- All events are related to products and users

```
File: /home/bernd/Downloads/eCommerce-archive/2019-Nov.csv
1 event_time,event_type,product_id,category_id,category_code,brand,price,user_id,user_session
2 2019-11-01 00:00:00 UTC,view,1003461,2053013555631882655,electronics.smartphone,xiaomi,489.07,520088904,4d3b30da-a5e4-49df-b1a8-ba5943fidd33
3 2019-11-01 00:00:00 UTC,view,5000088,2053013566100866035,appliances.sewing_machine,janome,293.65,530496790,8e5f4f63-366c-4f70-800e-ca7417414283
4 2019-11-01 00:00:01 UTC,view,17302664,205301355853497655,creed,28.31,561587266,755422e7-9040-477b-9bd2-6a6e8fd97387
5 2019-11-01 00:00:01 UTC,view,3601530,2053013563810775923,appliances.kitchen.washer_lg,712.87,518005591,3bf058cd-7892-48cc-8020-2f17e6debe7f
6 2019-11-01 00:00:01 UTC,view,1004775,2053013555631882655,electronics.smartphone,xiaomi,183.27,558856683,313628f1-68b8-460d-84f6-cec7a8796ef2
7 2019-11-01 00:00:01 UTC,view,1306894,2053013558920217191,computers.notebook.hp,360.09,520772689,816a59f3-f5ae-4ccd-9b23-82aa8c23d33c
8 2019-11-01 00:00:01 UTC,view,1306421,2053013558920217191,computers.notebook.hp,514.56,514028527,df8184cc-3694-4549-8c8c-6b5171877376
9 2019-11-01 00:00:02 UTC,view,15900005,2053013558190408249,ronnell,30.86,518574284,5e6ef132-4d7c-4730-8c7f-85aa4082588f
10 2019-11-01 00:00:02 UTC,view,12708937,205301355359896355,michelin,72.72,532364121,0a899268-31eb-46de-898d-09b2de950b24
11 2019-11-01 00:00:02 UTC,view,1004258,2053013555631882655,electronics.smartphone,apple,732.07,532647354,d2d3d2c6-631d-489e-9fb5-06f340b85be0
12 2019-11-01 00:00:03 UTC,view,17200570,2053013559792632471,furniture.living_room.sofa,437.33,519700043,aa806035-b14c-45af-9530-cd4d1849be3e
13 2019-11-01 00:00:03 UTC,view,2701517,2053013563911439225,appliances.kitchen.refrigerators,155.11,518427361,c80b0096-247f-4044-9c91-bb5f38c6af9b
14 2019-11-01 00:00:03 UTC,view,16700260,2053013559901684381,furniture.kitchen.chair,31.64,56625262,173d7b72-1db7-4638-8207-be8148bf3c9f
15 2019-11-01 00:00:04 UTC,view,34600011,2060981320581906480,20.54,512416379,4dfe2c67-e537-4dc2-ae69-0be5263dd091
16 2019-11-01 00:00:05 UTC,view,46000558,2053013563944993659,appliances.kitchen.dishwasher,samsung,411.83,526595547,aab33a9a-29c3-4d50-84c1-8a2bc9256104
17 2019-11-01 00:00:05 UTC,view,24900193,2053013562183385881,1.09,512651494,foa3c815-f51a-46fe-9484-cb58e35edaf
18 2019-11-01 00:00:07 UTC,view,27400066,2053013563391345499,8.55,551001950,3f6112f1-5695-4e88-bb0a-49f9e36658ff
19 2019-11-01 00:00:07 UTC,view,51005003,2053013553375346967,xiaomi,22.68,520037415,f54fa96a-f3f2-43ac-99a4-fcb2a4490d36
20 2019-11-01 00:00:07 UTC,view,1004566,2053013555631882655,electronics.smartphone.huawei,164.84,566265908,52c2c76c-b79e-4794-86ff-badc76d35f5a
```

# Pandas vs Polars

## Pandas DataFrame:

```
import pandas as pd

df = pd.read_csv("2019-Nov.csv")

df_filtered = df[df["event_type"] == "purchase"]

df_grouped = df_filtered
    .groupby("brand") ["price"]
    .mean()
    .reset_index()

df_sorted = df_grouped
    .sort_values("price", ascending=False)

print(df_sorted)
```

	brand	price
647	dynacord	1919.480000
1823	rado	1899.660000
1641	omabelle	1852.267248
33	aerosystem	1801.820000
1714	peda	1724.247857
...	...	...
969	heinz	1.180000
239	banbao	1.180000
703	enlightenbrick	0.970000
863	gerber	0.960385
585	dfz	0.900000

[2486 rows x 2 columns]

Elapsed time: 1m 56s  
Percent CPU: 100%  
Maximum resident set size: 18.5 GB

# Pandas vs Polars

## Polars DataFrame:

```
import polars as pl

df = (
    pl.read_csv("2019-Nov.csv")
    .filter(pl.col("event_type") == "purchase")
    .group_by("brand")
    .agg(pl.col("price").mean())
    .sort("price", descending=True)
)

print(df)
```

shape: (2\_488, 2)

brand	price
---	---
str	f64
dynacord	1919.48
rado	1899.66
omabelle	1852.267248
aerosystem	1801.82
peda	1724.247857
...	...
banbao	1.18
heinz	1.18
enlightenbrick	0.97
gerber	0.960385
dfz	0.9

Elapsed time: 13s

Percent CPU: 900%

Maximum resident set size: 21 GB

POLARS\_MAX\_THREADS env var can control CPU usage



inovex

# Polars LazyFrame

```
import polars as pl

lf = (
    pl.scan_csv("2019-Nov.csv")
    .filter(pl.col("event_type") == "purchase")
    .group_by("brand")
    .agg(pl.col("price").mean())
    .sort("price", descending=True)
)
```

```
print(lf.explain())
```

```
df = lf.collect()
```

```
print(df)
```

```
SORT BY [col("price")]
AGGREGATE
  [col("price").mean()] BY [col("brand")]
FROM Csv SCAN 2019-Nov.csv
PROJECT 3/9 COLUMNS
SELECTION: [(col("event_type")) == (String(purchase))]
```

shape: (2\_488, 2)

brand	price
---	---
str	f64
dynacord	1919.48
rado	1899.66
omabelle	1852.267248
aerosystem	1801.82
peda	1724.247857
...	...
banbao	1.18
heinz	1.18
enlightenbrick	0.97
gerber	0.960385
dfz	0.9

Elapsed time: 5s

Percent CPU: 1033%

Maximum resident set size: 9 GB

# Polars LazyFrame Info

LazyFrame doesn't run each query line-by-line, but instead processes the full query end-to-end

- Apply automatic **query optimization**
- Catch schema errors **before** processing the data
- Work with larger than memory datasets using **streaming**



```
import polars as pl
lf = (
    ...
)
print(lf.explain(streaming=True))
df = lf.collect(streaming=True)
```

```
--- STREAMING
SORT BY [col("price")]
AGGREGATE
    [col("price").mean()] BY [col("brand")]
FROM Csv SCAN 2019-Nov.csv
PROJECT 3/9 COLUMNS
SELECTION: [(col("event_type")) == (String(purchase))]
--- END STREAMING

DF []; PROJECT */0 COLUMNS; SELECTION: "None"
```

# Polars Expressions & Transformations

- Expressions
  - Cache-Optimal String Functions
  - Folds
  - Window Functions
  - First-class support for Lists & Arrays
  - Structs to work with multiple columns
- Transformations
  - Joins
  - Pivots
  - Melts
  - Time series
  - Concatenation



# Visualization

- hvPlot (used by built-in plot)
- Matplotlib (converts Series to numpy arrays)
- Seaborn (Python dataframe API standard)
- Plotly
- Altair



# Python User Defined Functions



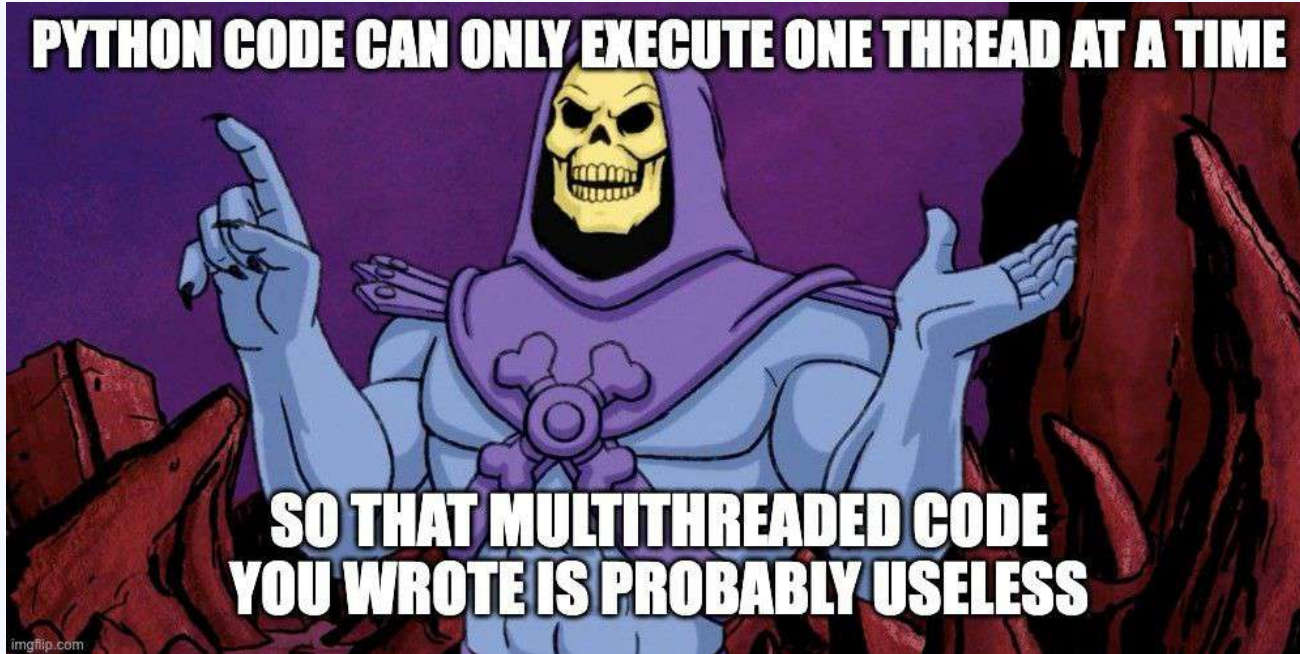
- `map_batches`: passing the Series in an expression to a third party library (do not use with `group_by`)
- `map_elements` (f.k.a. `apply`): passes elements of the column to the Python function

```
df.select(  
    pl.col("tracking_data")  
        .map_batches(lambda s: TrackingNeuralNetwork.predict(s.to_numpy()))  
        .alias("wishes_and_desires"),  
    pl.col("credit_card_encrypted")  
        .map_elements(lambda v: decrypt(key, v))  
        .alias("credit_card")  
)
```





## GIL explained:





<https://github.com/meldron/polars-expedition>



# Rust Extensions with pyo3-polars

- Create Rust extensions to circumvent the GIL (👹)
- Uses [PyO3](#) (11k★) and [maturin](#) (3k★)
- Outputs wheel files for specific architectures / targets



```
[package]
name = "polars_encrypt"
version = "0.1.0"
edition = "2021"

[lib]
name = "polars_encrypt"
crate-type = ["cdylib"]

[dependencies]
polars = { version = "0.38", features = [...] }
polars-core = { version = "0.38" }
polars-lazy = { version = "0.38" }
pyo3 = { version = "0.20", features = ["extension-module", "abi3-py310"] }
pyo3-polars = { version = "0.12", features = ["lazy"] }
```

```
$ maturin build --release
```

```
🔗 Found pyo3 bindings with abi3 support for Python ≥ 3.10
```

```
🐸 Not using a specific python interpreter
```

```
Compiling...
```

```
Finished release [optimized] target(s) in 49.26s
```

```
📦 Built wheel for abi3 Python ≥ 3.10 to
target/wheels/polars_encrypt-0.1.0-cp310-abi3-manylinux_2_34_x86_64.whl
```

# PyO3 Polars Example Module



```
fn parallel_encrypt_data_frame(
    df: DataFrame,
    col: &str,
    password: &str,
) -> PolarsResult<DataFrame> { ... }

#[pyfunction]
fn parallel_encrypt(pydf: PyDataFrame, col: &str, password: &str) -> PyResult<PyDataFrame> {
    let df: DataFrame = pydf.into();
    let df_encrypted = parallel_encrypt_data_frame(df, col, password).map_err(PyPolarsErr::from)?;
    Ok(PyDataFrame(df_encrypted))
}

#[pymodule]
fn extend_polars(_py: Python, m: &PyModule) -> PyResult<()> {
    m.add_function(wrap_pyfunction!(parallel_encrypt, m)?);
    m.add_function(wrap_pyfunction!(parallel_decrypt, m)?);
    m.add_function(wrap_pyfunction!(lazy_parallel_encrypt, m)?);
    m.add_function(wrap_pyfunction!(lazy_parallel_decrypt, m)?);
    Ok(())
}
```

## map\_elements vs PyO3

Encrypt & Decrypt **916\_939** lines of 9 chars:

### map\_elements:

Elapsed time: 14s

Percent CPU: 101%

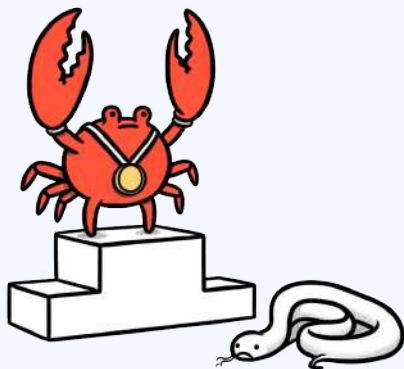
Maximum resident set size: 5GB

### PyO3 module:

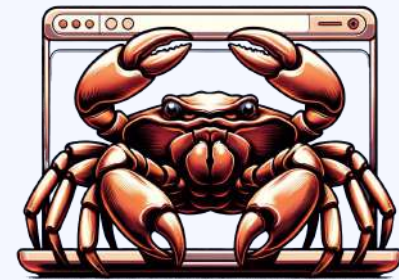
Elapsed time: 1s

Percent CPU: 500%

Maximum resident set size: 0.6GB



# Polars in the Browser (WASM)



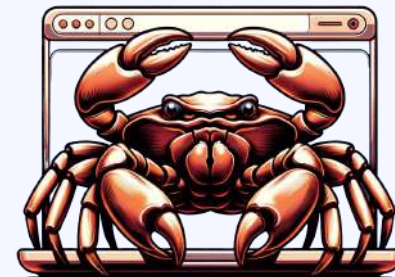
- Polars can be compiled to WebAssembly (WASM)
- Not fully supported (features have to be disabled)
- Basic DataFrame and CSV reader are working

```
[dependencies.polars]
version = "0.37.0"
default-features = false
features = [
  "abs", "regex",
  "diff", "dtype-full",
  "round_series", "lazy",
  "mode", "product",
  "rank", "reinterpret", "rows",
  "strings", "semi_anti_join",
  "unique_counts", "csv",
  # "parquet", "ipc", "performant" :(
]
```

```
$ wasm-pack build
[INFO]: 🎯 Checking for the Wasm target...
[INFO]: 🌀 Compiling to Wasm...
Compiling..
Finished release [optimized] target(s) in 2m 32s
[INFO]: 📦 Installing wasm-bindgen...
[INFO]: ✨ Done in 2m 35s
[INFO]: 📦 Your wasm pkg is ready to publish at /tmp/polars-wasm/pkg.
```

```
$ ls /tmp/polars-wasm/pkg
README.md package.json
polars_wasm_bg.js polars_wasm_bg.wasm.d.ts
polars_wasm_bg.wasm (13 MB / 2 MB gzip)
polars_wasm.d.ts polars_wasm.js
```

# Polars in the Browser (WASM)



```
#[wasm_bindgen]
pub fn describe(csv_data: &str, date_cols_js: JsValue) -> Result<String, String> {
    let cursor = Cursor::new(csv_data.as_bytes());
    let df_result = CsvReader::new(cursor).infer_schema(None).finish();
    let df = match df_result {
        Ok(df) => df,
        Err(err) => return Err(err.to_string()),
    };

    let date_cols: HashMap<String, String> = from_value(date_cols_js).map_err(|e| e.to_string())?;
    let mut map: HashMap<String, Stats> = HashMap::new();

    for series in df.get_columns() { ... }

    let result = to_string(&map).map_err(|e| e.to_string())?;
    Ok(result)
}
```

## SQL Context

- SQLContext allows mapping DataFrames and LazyFrames names to their datasets
- **No** separate SQL engine
- SQL queries become polars expressions
- Polars does not support the full SQL Language





## SQL Context Support



### Supports:

- Write a `CREATE` statements
- Write a `SELECT` statements with all generic elements (`GROUP BY`, `WHERE`, `ORDER`,...)
- Write Common Table Expressions (`WITH table AS`)
- Show an overview of all tables `SHOW TABLES`

### Not Supported:

- `INSERT`, `UPDATE`, `DELETE`
- Table aliasing
- Meta queries (`ANALYZE`, `EXPLAIN`)

# SQL Example

```
ctx = pl.SQLContext()
e_commerce_events = pl.scan_csv("2019-Nov.csv")
ctx.register("e_commerce_events", e_commerce_events)
```

```
lf = ctx.execute(
    """
    WITH purchases AS (
        SELECT
            product_id, brand, price FROM e_commerce_events
        WHERE event_type = 'purchase'
    )
    SELECT
        product_id, brand, count(*) AS purchase_count,
        min(price) AS price_min, avg(price) AS price_avg,
        max(price) AS price_max,
        stdev(price) AS price_stdev
    FROM purchases
    GROUP BY product_id, brand
    HAVING purchase_count > 10
    ORDER BY price_stdev DESC
    LIMIT 10
    """,
    eager=False,
)
```

```
SORT BY [col("price_stdev")]
FAST_PROJECT: [product_id, brand, purchase_count, price_min,
price_avg, price_max, price_stdev]
FILTER [(col("purchase_count")) > (10)] FROM
```

## AGGREGATE

```
[len().alias("purchase_count"), col("price").min().alias("price_min"),
col("price").mean().alias("price_avg"),
col("price").max().alias("price_max"),
col("price").std().alias("price_stdev")]
BY [col("product_id"), col("brand")] FROM
FAST_PROJECT: [product_id, brand, price]
```

```
Csv SCAN 2019-Nov.csv
PROJECT 4/9 COLUMNS
SELECTION: [(col("event_type")) == (String(purchase))]
```

product_id	brand	purchase_count	price_min	price_avg	price_max	price_stdev
i64	str	u32	f64	f64	f64	f64
2200982	canon	33	1389.97	1670.702121	1976.92	286.925209
1004159	samsung	38	769.13	947.364211	1253.07	236.495904
15100141	null	22	493.96	1461.552727	1569.92	227.148752
15100239	ostamebel	35	308.86	650.714	823.7	220.342035
2200486	nikon	11	1261.27	1434.444545	1698.89	209.794349
1801795	sony	21	2059.0	2334.792857	2445.11	178.734199
1801938	sony	29	1157.79	1449.722069	1544.16	167.64585
1306571	acer	29	1801.82	2083.653448	2312.8	166.756888
2701627	lg	18	1645.81	1871.702778	2004.43	141.609503
1305215	apple	24	1209.55	1326.735833	1503.49	138.539943

# SQL Example

```
ctx = pl.SQLContext()
e_commerce_events = pl.scan_csv("2019-Nov.csv")
ctx.register("e_commerce_events", e_commerce_events)

lf = ctx.execute(
    """
    WITH purchases AS (
        SELECT
            product_id, brand, price FROM e_commerce_events
            WHERE event_type = 'purchase'
    )
    SELECT
        product_id, brand, count(*) AS purchase_count,
        min(price) AS price_min, avg(price) AS price_avg,
        max(price) AS price_max,
        stdev(price) AS price_stdev
    FROM purchases
    GROUP BY product_id, brand
    HAVING purchase_count > 10
    ORDER BY price_stdev DESC
    LIMIT 10
    """,
    eager=False,
)
```

35



```
lf = pl.scan_csv("2019-Nov.csv")
purchases = lf
    .filter(pl.col("event_type") == "purchase")
    .select(
        [
            pl.col("product_id"),
            pl.col("brand"),
            pl.col("price")
        ]
    )
result = (
    purchases.group_by(["product_id", "brand"])
    .agg(
        [
            pl.len().alias("purchase_count"),
            pl.min("price").alias("price_min"),
            pl.mean("price").alias("price_avg"),
            pl.max("price").alias("price_max"),
            pl.std("price").alias("price_stdev"),
        ]
    )
    .filter(pl.col("purchase_count") > 10)
    .sort(by="price_stdev", descending=True)
    .limit(10)
)
```

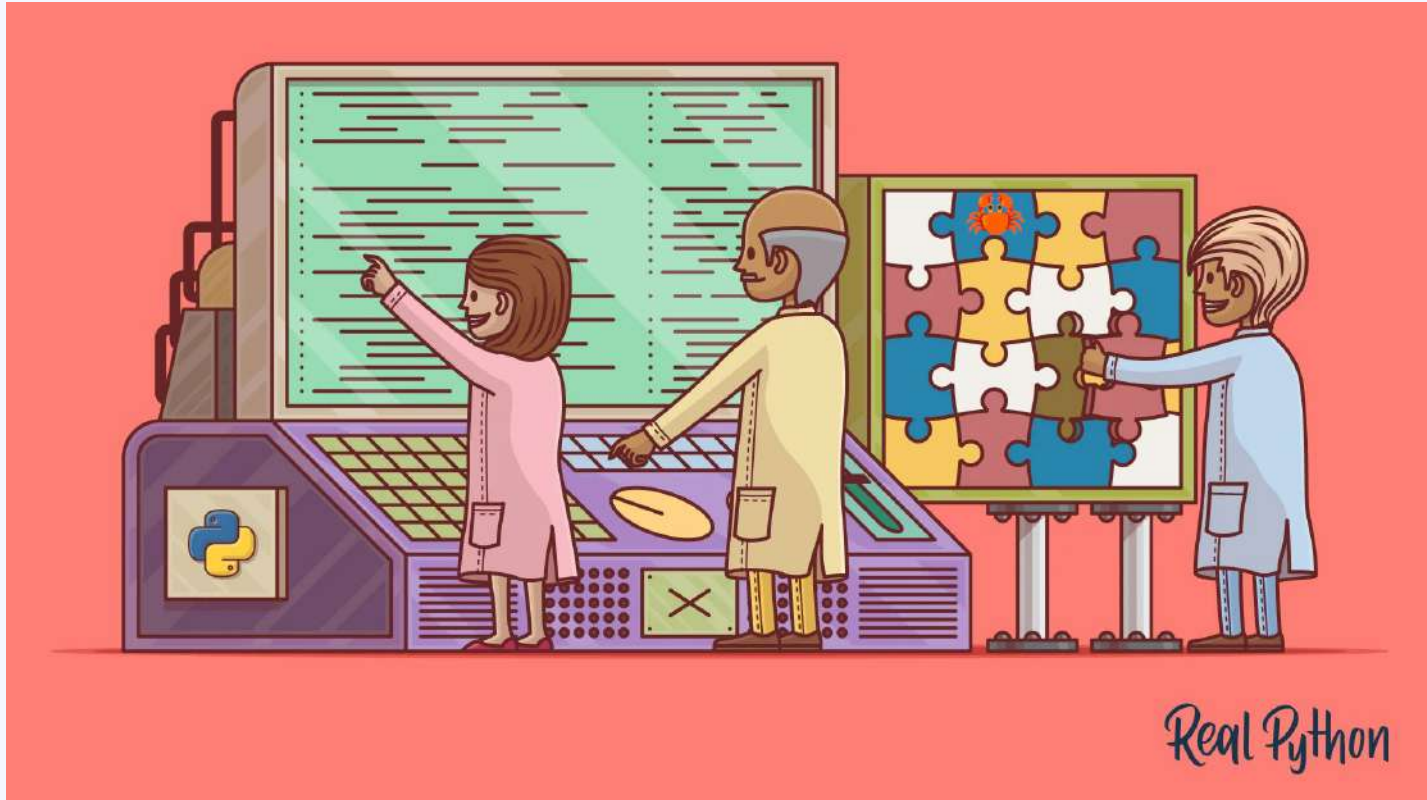
## polars-cli

- Run SQL queries on datasets from your command line
- Input formats: csv, json, parquet, IPC/Apache Arrow
- Output formats: csv, json, parquet, arrow, table, markdown



```
polars -o csv -c \  
  "WITH purchases AS (SELECT product_id, brand, price FROM  
  read_parquet('2019-Nov.parquet') WHERE event_type = 'purchase')  
  SELECT product_id, brand, count(*) AS c, avg(price) AS avg_price  
  FROM purchases GROUP BY product_id, brand ORDER BY c DESC"
```

## Why should I use this and not a Python script?





# DuckDB

## Digression: DuckDB

- DuckDB is a fast in-process analytical database
- [Github](#): 15k ★
- License: [MIT](#)
- Feature-Rich
  - ACID guarantees
  - Multi-Version Concurrency Control (MVCC)
  - Complex queries with vectorized execution
  - nested correlated subqueries
  - window functions
  - collations
  - complex types (arrays, structs)

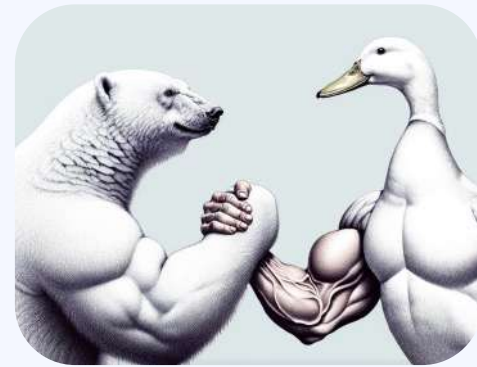


# Polars / DuckDB Integration

```
import polars as pl
import duckdb

df = pl.DataFrame(
    {
        "A": [1, 2, 3, 4, 5],
        "fruits": ["🍌", "🍏", "🍌", "🍏", "🍌"],
        "B": [5, 4, 3, 2, 1],
    }
)

duckdb.sql("SELECT * FROM df").show()
```



```
df = duckdb.sql("""
    SELECT 1 AS id, 'banana' AS fruit
    UNION ALL
    SELECT 2, 'apple'
    UNION ALL
    SELECT 3, 'mango'""")
df.pl()
print(df)
```

## Resources

- <https://pola.rs/> - Project website
- [What is Polars?](#) - Polars explained in 90s by the creator
- Podcasts: [TalkPython](#), [RealPython](#), [Rustacean Station](#)
- <https://github.com/meldron/polars-expedition>





# Thanks a lot!



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