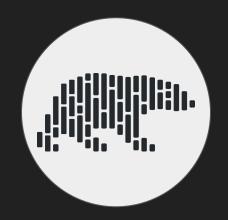
HELLO POLARS!

LIGHTNING-FAST DATAFRAME LIBRARY FOR RUST AND PYTHON



Antonio Bevilacqua 18/10/2022





ANTONIO BEVILACQUA
POSTDOCTORAL RESEARCHER @INSIGHT-CENTRE, UCD

thisisanton.io github/b3by

CONTENT

BRIEF INTRODUCTION ABOUT POLARS [key concepts]

POLARS IS <u>NOT</u> PANDAS* [key differences]

PERFORMANCE & BENCHMARKS
[hands-on]
[H2O.ai]

DATAFRAME LIBRARY

DATAFRAME LIBRARY
IN-MEMORY QUERY ENGINE

DATAFRAME LIBRARY
IN-MEMORY QUERY ENGINE
DBMS-ESQUE LAYER

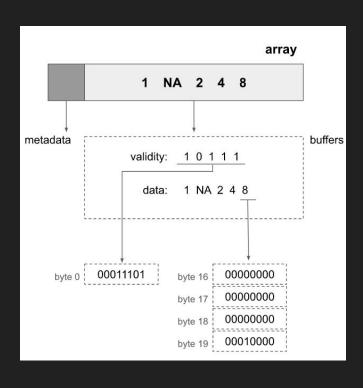
DATAFRAME LIBRARY
IN-MEMORY QUERY ENGINE
DBMS-ESQUE LAYER

BASED ON THE SAME PANDAS CONCEPT OF DATAFRAMES FILLING THE GAPS BETWEEN PANDAS AND SPARK

POLARS USES **APACHE ARROW** COLUMNAR FORMAT
[in-memory optimizations]
[parallel by default]

DATA STRUCTURES BUILT IN CONTIGUOUS MEMORY LOCATIONS IDEAL FOR BIT MASKING AND MULTITHREADING

NUMERIC ARRAYS



NUMERIC ARRAYS

VALIDITY
ENDIANNESS IS A
BIT CONFUSING

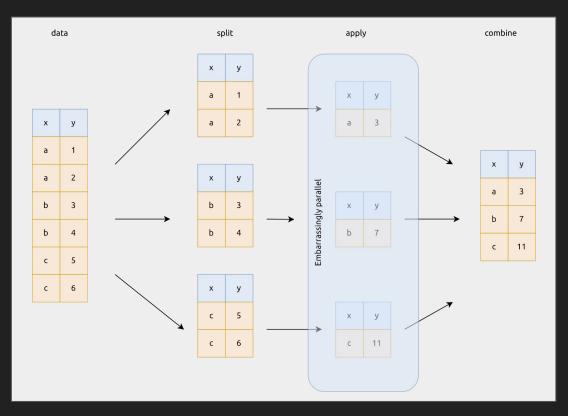


STRING ARRAYS

data: [str]	f	o	o	Ь	a	Г	h	a	m
offsets: [i64]	0	2	5	8					
validity bits	01	1011							

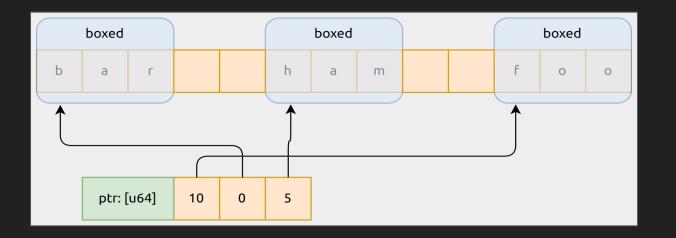
OFFSET BITS POINT TO VALUE INDEXES IN MEMORY

STRING ARRAYS



NUMPY REPRESENTATION

STRING ARRAYS



PANDAS USES NUMPY OBJECTS ALLOCATED ON THE HEAP SOME TIME WASTED ON LOOKUP & CACHE MISS :(

POLARS APIs

AVAILABLE FOR PYTHON & RUST PROVIDES **EAGER** APIs AND **LAZY** APIs

EAGER

QUERY PIPELINES
ARE EVALUATED
ON THE FLY (LIKE
PANDAS)

LAZY

QUERY PIPELINES
ARE OPTIMIZED
FIRST AND
EVALUATED ONLY
WHEN COLLECTED

POLARS APIs

```
import polars as pl

pl.read_csv('iris.csv')
   .filter(pl.col('sepal_length') > 5)
   .groupby('species')
   .agg(pl.all().sum())

import polars as pl

pl.read_csv('iris.csv')
   .lazy()
   .filter(pl.col('sepal_length') > 5)
   .groupby('species')
   .agg(pl.all().sum())
   .collect()
```

POLARS VS PANDAS

POLARS DOES NOT HAVE INDEXES
[indexing is considered to be an anti-pattern]

POLARS USES APACHE ARROWS vs. NUMPY NDARRAYS [we already talked about that]

POLARS HAS LAZY APIs & IS MULTITHREADING-READY [some frameworks try to fill the gap in pandas]

POPULARITY AND ADOPTION



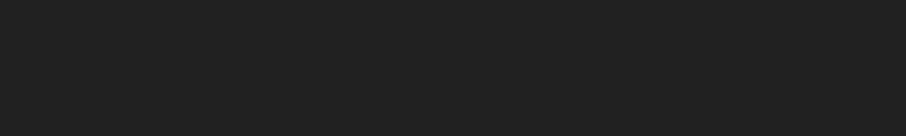




35.6K	STARS	8.6K		
89	RELEASES	10		
30.3K	COMMITS	4.5K		
15.2K	FORKS	471		

DON'T RESIST THE HYPE!





LET'S LOOK AT SOME NUMBERS NOW!

BENCHMARK SETUP

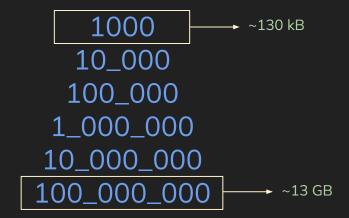
KAGGLE DATASET OF TRANSACTIONS FROM ONLINE STORE* (LARGE: 9GB + 5GB)

	event_time	event_type	product_id	category_id	category_code	brand	price	user_id	user_session
i64	str	str	i64	i64	str	str	f64	i64	str
0	"2019-10-01 00:	"view"	44600062	2103807459595387724	null	"shiseido"	35.79	541312140	"72d76fde-8bb3
1	"2019-10-01 00:	"view"	3900821	2053013552326770905	"appliances.env	"aqua"	33.2	554748717	"9333dfbd-b87a
2	"2019-10-01 00:	"view"	17200506	2053013559792632471	"furniture.livi	null	543.1	519107250	"566511c2-e2e3
3	"2019-10-01 00:	"view"	1307067	2053013558920217191	"computers.note	"lenovo"	251.74	550050854	"7c90fc70-0e80
4	"2019-10-01 00:	"view"	1004237	2053013555631882655	"electronics.sm	"apple"	1081.98	535871217	"c6bd7419-2748

^{*} https://www.kaggle.com/datasets/mkechinov/ecommerce-behavior-data-from-multi-category-store

BENCHMARK SETUP

PARTITIONS TESTED FOR BENCHMARKS (# ROWS)



BENCHMARK SETUP

QUERIES TESTED FOR BENCHMARKS SPLIT INTO GROUPS

DATA LOAD IN MEMORY

DATA SUMMARY

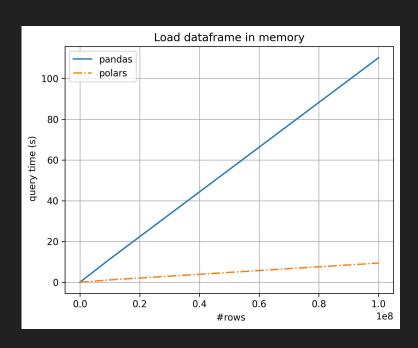
[describe, count values, count uniques, count nans...]

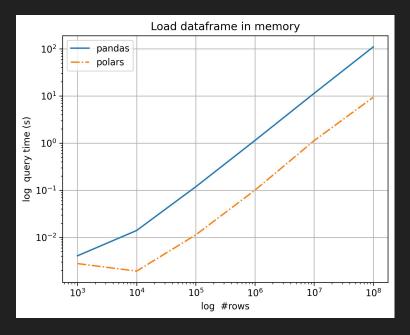
DATA ORDERING & FILTERING

[sorting columns, logical conditions...]

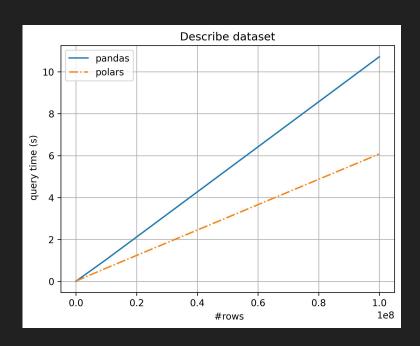
GROUPING

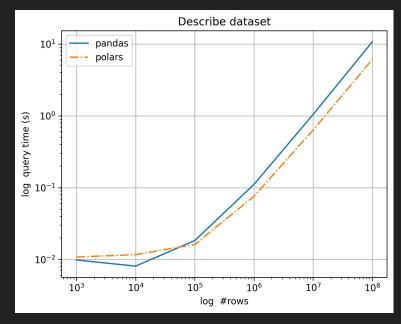
LOAD DATA





DESCRIBE DATA





GET COLUMN UNIQUE VALUES

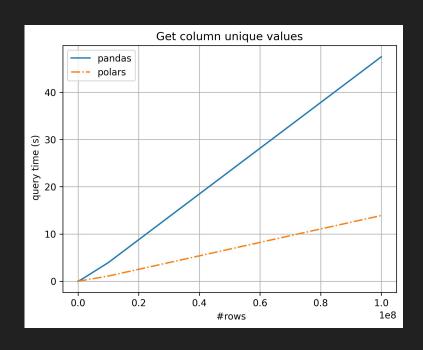
```
import polars as pl

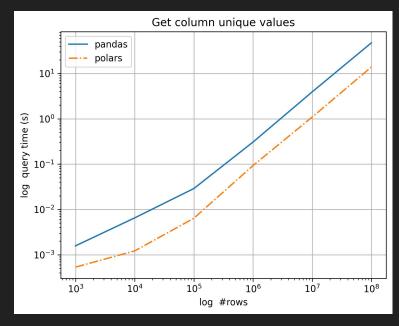
pl.read_csv(data.csv')
    .select([
    pl.col('*').unique().count()
])

import pandas as pd

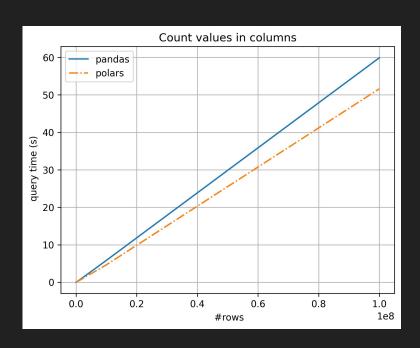
pd.read_csv('data.csv')
    .apply(λ col: len(col.uniques())
```

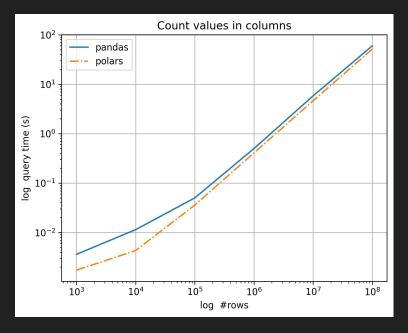
GET COLUMN UNIQUE VALUES



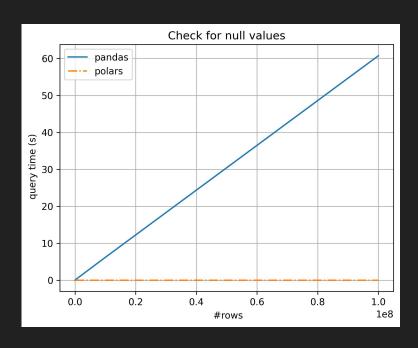


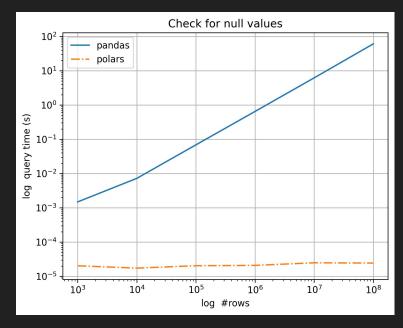
VALUE COUNTS



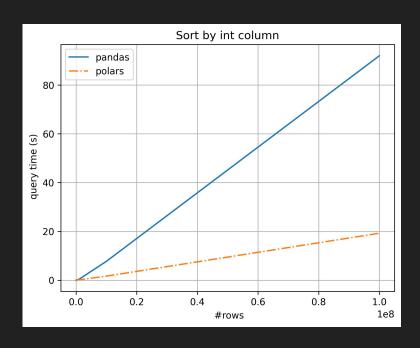


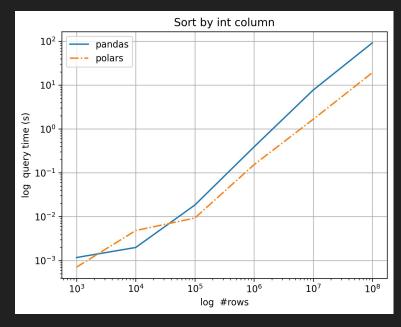
CHECK FOR NULL VALUES





SORT BY COLUMN (INT)





SORT BY COLUMN (DATETIME)

```
import polars as pl

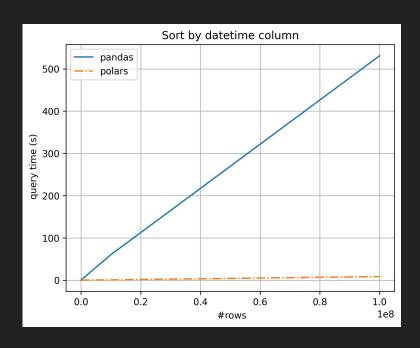
pl.read_csv(data.csv')
    .select([
    pl.col('event_time')
        .str
        .strptime(pl.Datetime, fmt='...')
        .sort()
])

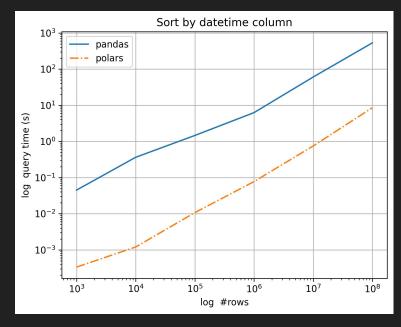
import pandas as pd

df = pd.read_csv('data.csv')

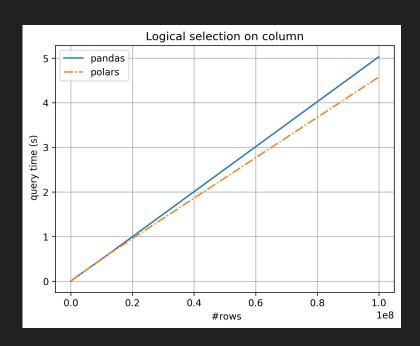
pd.to_datetime(df['event_time'])
        .sort_values()
```

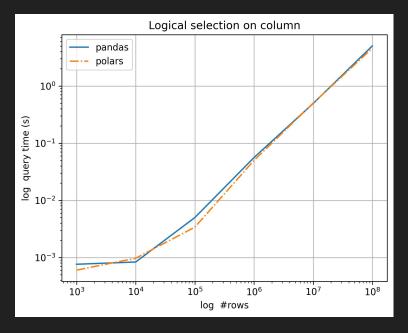
SORT BY COLUMN (DATETIME)





LOGICAL SELECTION





GROUPBY AGGREGATION

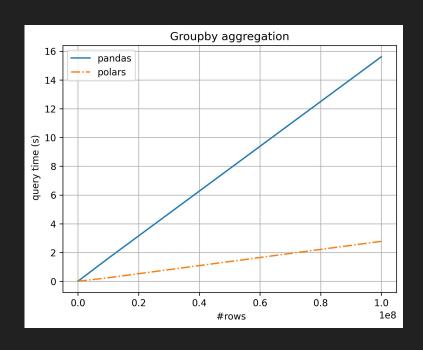
```
import polars as pl

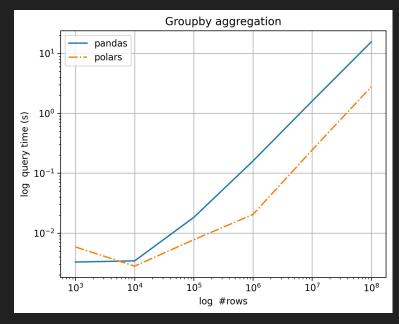
pl.read_csv(data.csv')
    .groupby('brand').agg([
    pl.col('price').min(),
    pl.col('price').max(),
    pl.col('price').std(),
    pl.col('price').mean()
])

import pandas as pd

pd.read_csv('data.csv')
    .groupby('brand')['price']
    .agg(['min', 'max', 'std', 'mean'])
    agg(['min', 'max', 'std', 'mean'])
```

GROUPBY AGGREGATION





LINKS WHERE I STOLE MY STUFF

OFFICIAL POLARS WEBSITE https://www.pola.rs/

APACHE ARROW FORMAT DOCS https://arrow.apache.org/docs/format/Columnar.html

H20 BENCHMARKS https://h2oai.github.io/db-benchmark/

MORE ON ARROWS

https://blog.djnavarro.net/posts/2022-05-25_arrays-and-tables-in-arrow/

THANK YOU!

```
?? | /* */
```