Pandas 2, Polars or Dask? An update from June

PyDataGlobal 2023 Talk

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We are Ian Ozsvald & Giles Weaver

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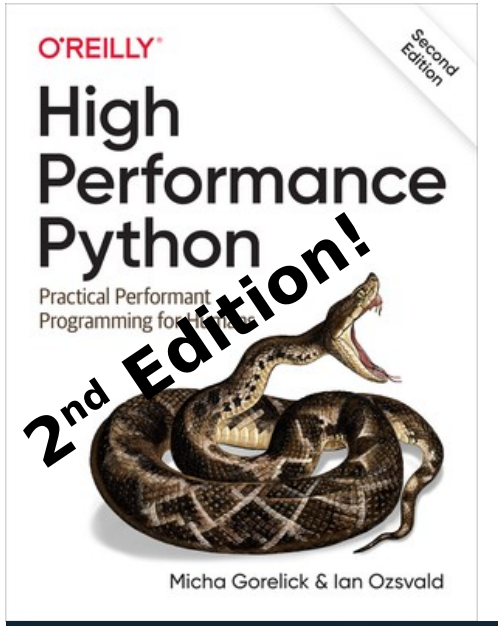
- Data Scientist



Part of **PyData - 227 groups**

PyData London Meetup

London, 17, United Kingdom

13,447 members Public group

Organized by **NumFOCUS, Inc.** and **15 others**

Office for National Statistics

Shell

Man Group

Hotels.com™

'Pandas 2.1.3, Polars 0.19.17'

Dask 2023.11.0

3 interesting DataFrame libraries

- Lots of change in the ecosystem in recent years
- Which library should you use? **What do you use?**
- **Using Polars over 7 months**
- We benchmark. All benchmarks are lies

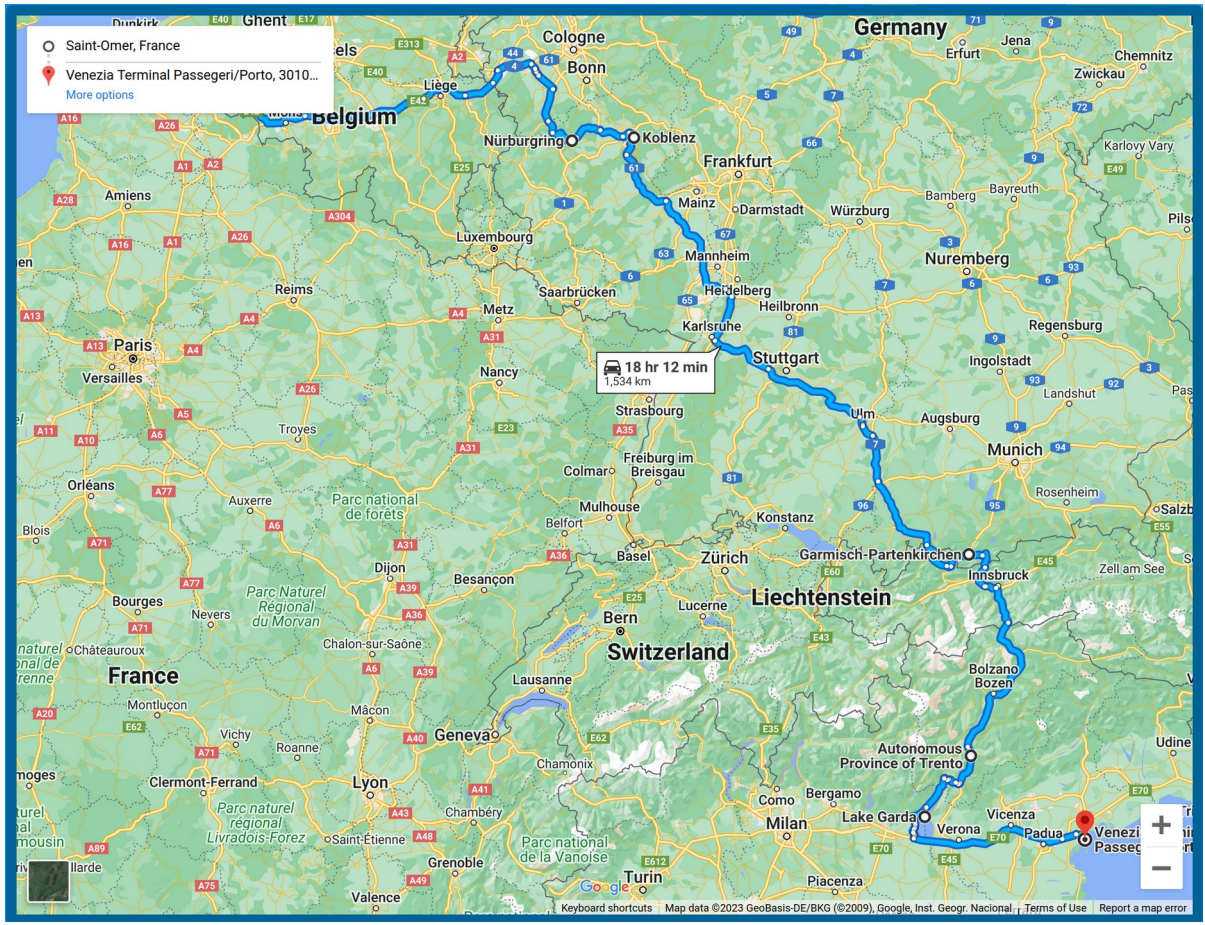
https://bit.ly/JustGivingIan

Motoscape Charity Rally

Rob, Edd and Ian's fundraiser for Parkinson's UK

MOTOSCAPE BANGER RALLY 2023, 2 September 2023

- Ian - "Let's do something silly"
- September 2023 (4 mo)
- 2,000 mile round trip <£1k car
- Ideally it shouldn't explode



https://www.check-mot.service.gov.uk/results?registration=cn05hjc

Car Test Data (UK DVLA)

- 17 years of roadtest pass or fails
- 30M vehicles/year, [C|T]SV text files
- Text→Parquet made easy with Dask
- 600M rows in total

CN05 HJC

VOLVO V50

Check another vehicle

Colour
Blue

Fuel type
Diesel

Date registered
10 March 2005

MOT valid until
17 April 2024

Date tested
12 May 2022

PASS

Mileage
171,443 miles

Test location
▶ View test location

MOT test number
9400 3587 8901

Expiry date
8 June 2023

test_date	test_class_id	test_type	test_result	test_mileage	make	model	colour	fuel_type	cylinder_capacity	first_use_date
2022-05-12 00:00:00	4	NT	F	171443	VOLVO	V50	BLUE	DI	1997	2005-03-10 00:00:00
2022-05-12 00:00:00	4	RT	P	171443	VOLVO	V50	BLUE	DI	1997	2005-03-10 00:00:00

Pandas 2 – what's new?

- Pandas 15 years old, NumPy based
- PyArrow first class alongside NumPy
- Internal clean-ups so less RAM used
- Copy on Write (off by default), faster & cheaper with it on

PyArrow vs NumPy – which to use?

Backend	String dtype	GroupBy Arrow can be slower

APACHE ARROW	`%timeit dfpda['make'].str.len()`
	`# e.g. TOYOTA, VOLKSWAGEN`
	`1.08 s ± 5.19 ms per loop (mean ± s`
		`%timeit dfpda.groupby('cylinder_capacity')['test_mileage'].mean()`
		✓ 20.0s
		`2.5 s ± 44.3 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)`

NumPy	`%timeit dfpdn['make'].str.len()`
	`8.18 s ± 44.4 ms per loop (mean ±`
		`%timeit dfpdn.groupby('cylinder_capacity')['test_mileage'].mean()`
		✓ 9.8s
		`1.23 s ± 12.6 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)`

PERF: group by manipulation is slower with new arrow engine #52070

Closed · 3 tasks done

NumPy strings expensive in RAM e.g.
82M rows 39GB NumPy, 11GB Arrow

NumExpr & bottleneck both installed
Checks for identical results in notebook

By [ian]@ianozsvald[.com] and giles@wvr-consulting.co.uk @gilesweaver

Ian Ozsvald

```
pip install ipython-memory-usage
```

Default Copy on Write == False

```
df2 = dfpdn.rename(columns={'make': 'car_make'}). \
    assign(is_petrol = dfpdn['fuel_type'] == 'PE'). \
    drop(columns=['fuel_type'])
```

✓ 17.5s

```
In [4] used 8604.7 MiB RAM in 17.57s (system mean cpu 13%, single max cpu 100
                                    peaked 9657.1 MiB above final usage
```

```
assert df2.loc[0, 'test_mileage'] == 227219 # original value
df2.loc[0, 'test_mileage'] = 99  # this column (only) copied
assert df2.loc[0, 'test_mileage'] == 99
assert dfpdn.loc[0, 'test_mileage'] == 227219 # original unchanged
```

✓ 0.2s

```
In [5] used 625.6 MiB RAM in 0.25s (system mean cpu 16%, single max cpu 100%)
```

pandas

NumPy

3 defensive copies

Notably worse on NumPy than Arrow

17GB envelope over 17s

Not sure why +600MB here...

```
pd.options.mode.copy_on_write = True
```

Pandas Copy on Write == True

Common operations no longer trigger defensive copies
Copies made *when needed*
Code *may execute faster*
Less RAM may be used

Are there dragons hidden in this new feature?

```
df2 = dfpdn.rename(columns={'make': 'car_make'}). \
          assign(is_petrol = dfpdn['fuel_type'] == 'PE'). \
          drop(columns=['fuel_type'])
```

✓ 3.3s

```
In [4] used 79.5 MiB RAM in 3.35s (system mean cpu 0%, single max cpu 0%), pea
```

```
assert df2.loc[0, 'test_mileage'] == 227219 # original value
df2.loc[0, 'test_mileage'] = 99  # this column (only) copied
assert df2.loc[0, 'test_mileage'] == 99
assert dfpdn.loc[0, 'test_mileage'] == 227219 # original unchanged
```

✓ 0.4s

```
In [5] used 1329.6 MiB RAM in 0.48s (system mean cpu 29%, single max cpu 100%)
```

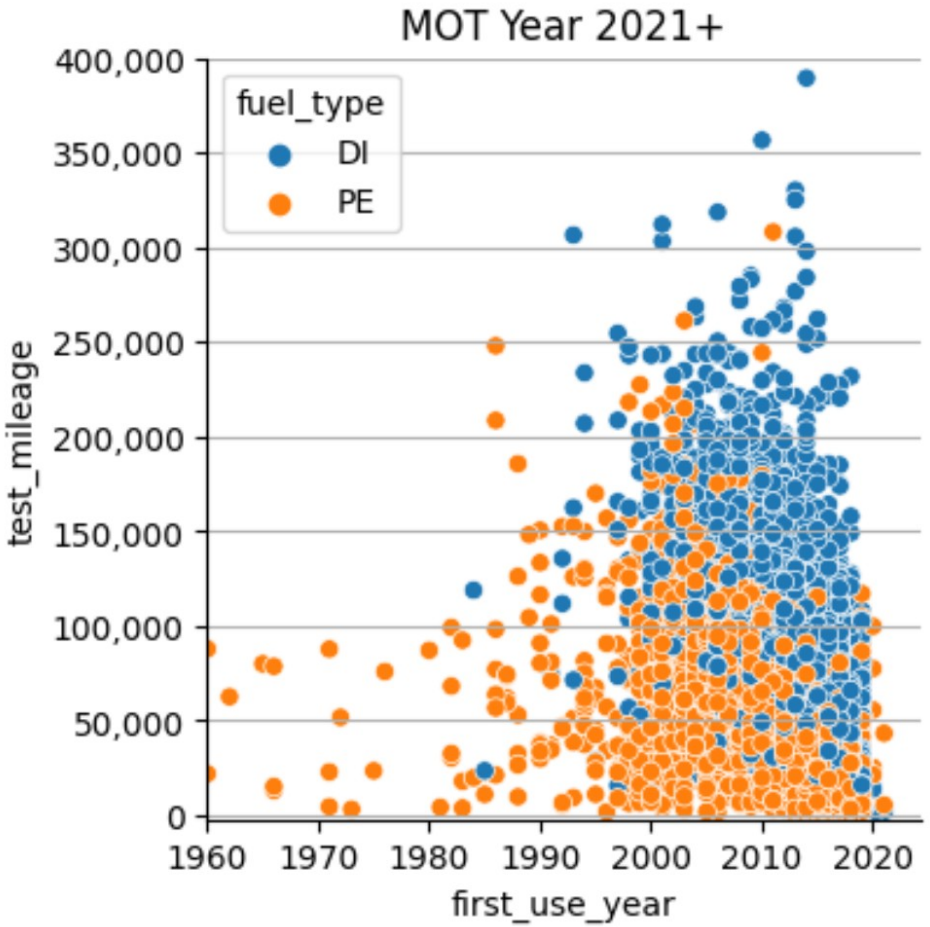
Pandas+Arrow, query, Seaborn

```
%%time
df_fuel = (
    dfpda.query('test_result=="P"')
    .sample(10_000)
    .assign(first_use_year=lambda dfx: dfx["first_use_date"].dt.year)[
        ["test_mileage", "fuel_type", "first_use_year"]
    ]
    .dropna()
    .query("fuel_type in ['PE', 'DI']")
)
```

✓ 20.1s

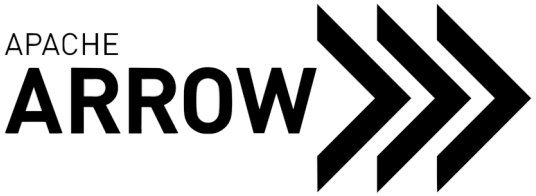
```
CPU times: user 13.4 s, sys: 7.03 s, total: 20.4 s
Wall time: 20.1 s
```

In 2023-06 this *took 14s*, so now it is slower



Polars – what's in it?

- Rust based, Python front-end, 3 years old
- Arrow (not NumPy)
- Inherently multi-core and parallelised
- Eager and Lazy API (+Query Planner)
- Beta out-of-core (medium data) support

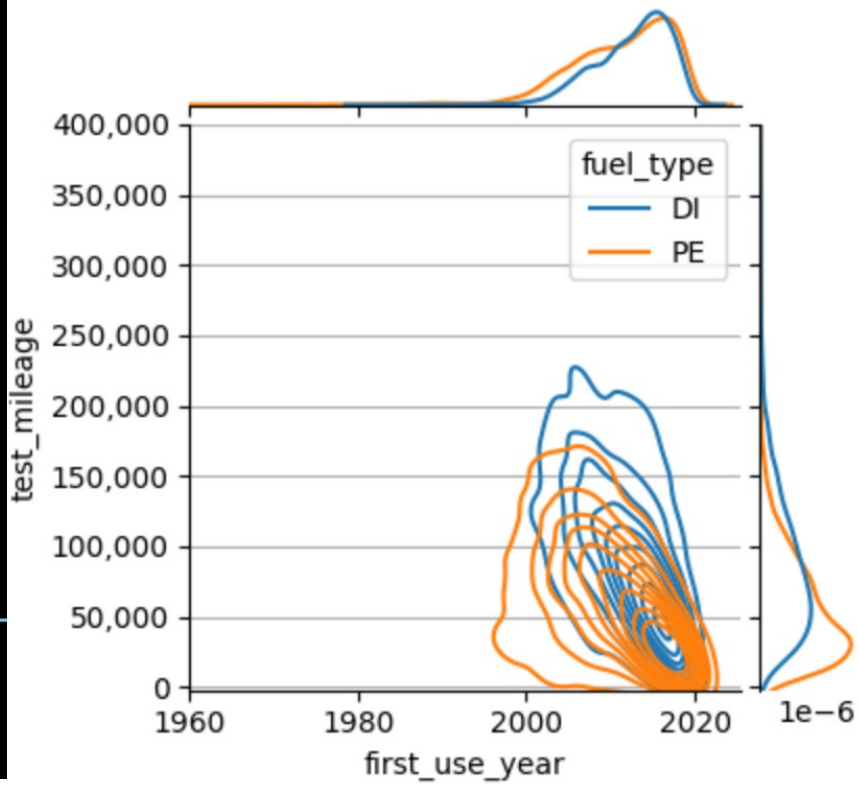


```
pip install ipython-memory-usage
```

Polars – same query & Seaborn

```
%%time
df_fuel = (
    dfple.filter(pl.col("test_result") == "P")
    .sample(10_000)
    .with_columns(pl.col("first_use_date").dt.year().alias("first_use_year"))
    .filter((pl.col("fuel_type").is_in({"PE", "DI"})))[
        ["test_mileage", "first_use_year", "fuel_type"]
    ]
)
```

```
CPU times: user 10.3 s, sys: 5.76 s, total: 16 s
Wall time: 2.69 s
```



50% faster than in 2023-06, the Lazy DataFrame can be even faster

A more advanced query

```
%%time
result = (
    dfpda.dropna(subset=["cylinder_capacity"])
    .groupby("make")["cylinder_capacity"]
    .agg(["median", "count"])
    .query("count > 10")
    .sort_values("median")
)
#"RuntimeWarning: Engine has switched to 'python'
# because numexpr does not support extension
# array dtypes"
result
```

```
CPU times: user 14.8 s, sys: 12.6 s, total: 27.3 s
Wall time: 27.4 s
```

Pandas+NumPy takes 13s using numexpr

50% slower than in 2023-16 for Pandas+Arrow, the numexpr warning is new

Enables the Query Planner optimisations

```
%%time
result = (
    dfple.lazy()
    .filter(pl.col("cylinder_capacity").is_not_null())
    .group_by(by="make")
    .agg(
        [
            pl.col("cylinder_capacity").median().alias("median"),
            pl.col("cylinder_capacity").count().alias("count"),
        ]
    )
    .filter(pl.col("count") > 10)
    .sort(by="median")
    .collect()
)
```

```
CPU times: user 25.3 s, sys: 2.69 s, total: 28 s
Wall time: 3.48 s
```

Polars eager (no “lazy() / collect()” call) takes 4.5s

First conclusions

- Pandas+Arrow *maybe better than* Pandas+NumPy
- Polars seems to be faster than Pandas+Arrow
- Pandas Copy on Write seems like a nice optimisation
- *All benchmarks are lies – your mileage will vary*

Volvo v50 lasts <24 hours

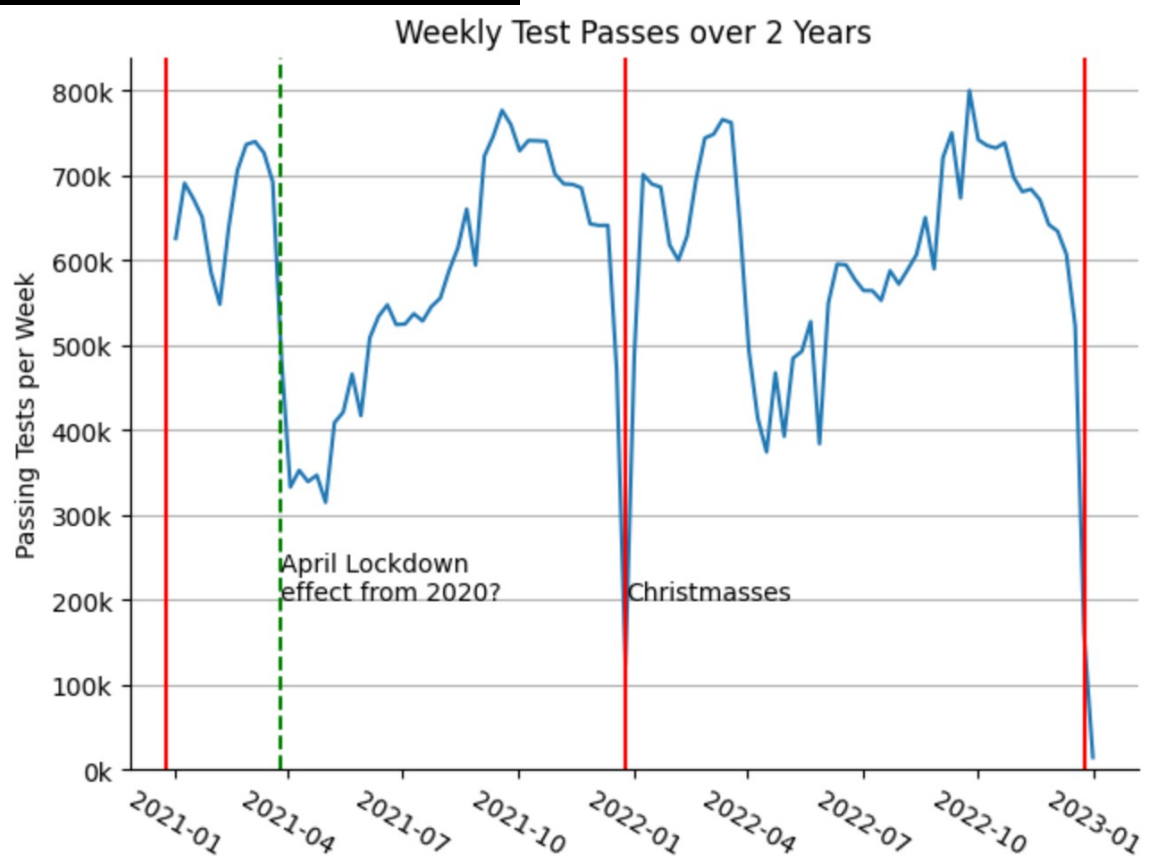
https://bit.ly/JustGivingIan

Resampling a timeseries

```
dfple = pl.read_parquet("../test_result_2021on.parquet")
```

```
dfple = dfple.with_columns((pl.col("test_result") == pl.lit("P")). \
    alias("passed"))
result = (
    dfple.sort(pl.col("test_date"))
    .group_by_dynamic("test_date", every="1w")
    .agg(pl.col("passed").sum())
)
```

```
used 60.4 MiB RAM in 6.76s (system mean cpu 55%, single max cpu 100%)
```



This dataset is in-RAM (2021-2022)

There's a **limit to how much we can instantiate into memory**, even if we're careful with sub-selection and dtypes

Scanning 640M rows of larger dataset

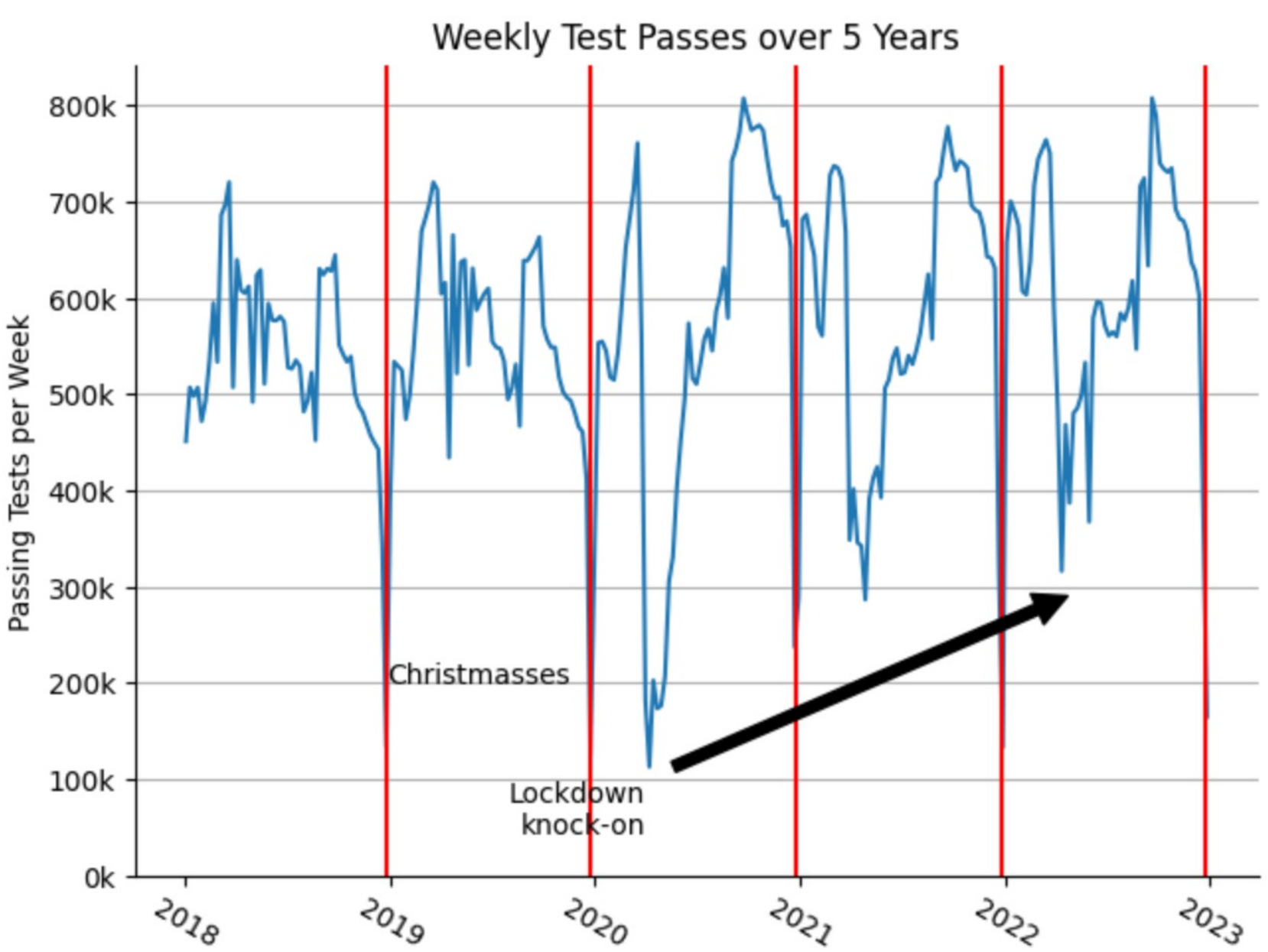
```
dfpll = pl.scan_parquet("../test_result.parquet/*.parquet")
```

Implicit Lazy DataFrame

```
result_lz = (
    dfpll.filter(pl.col("test_date") > datetime.datetime(2018, 1, 1))
    .with_columns((pl.col("test_result") == pl.lit("P")).alias("passed"))
    .sort(pl.col("test_date"))
    .group_by_dynamic("test_date", every="1w")
    .agg(pl.col("passed").sum())
    .collect()
)
```

13 seconds, 640M rows, circa 850 partitions (files)

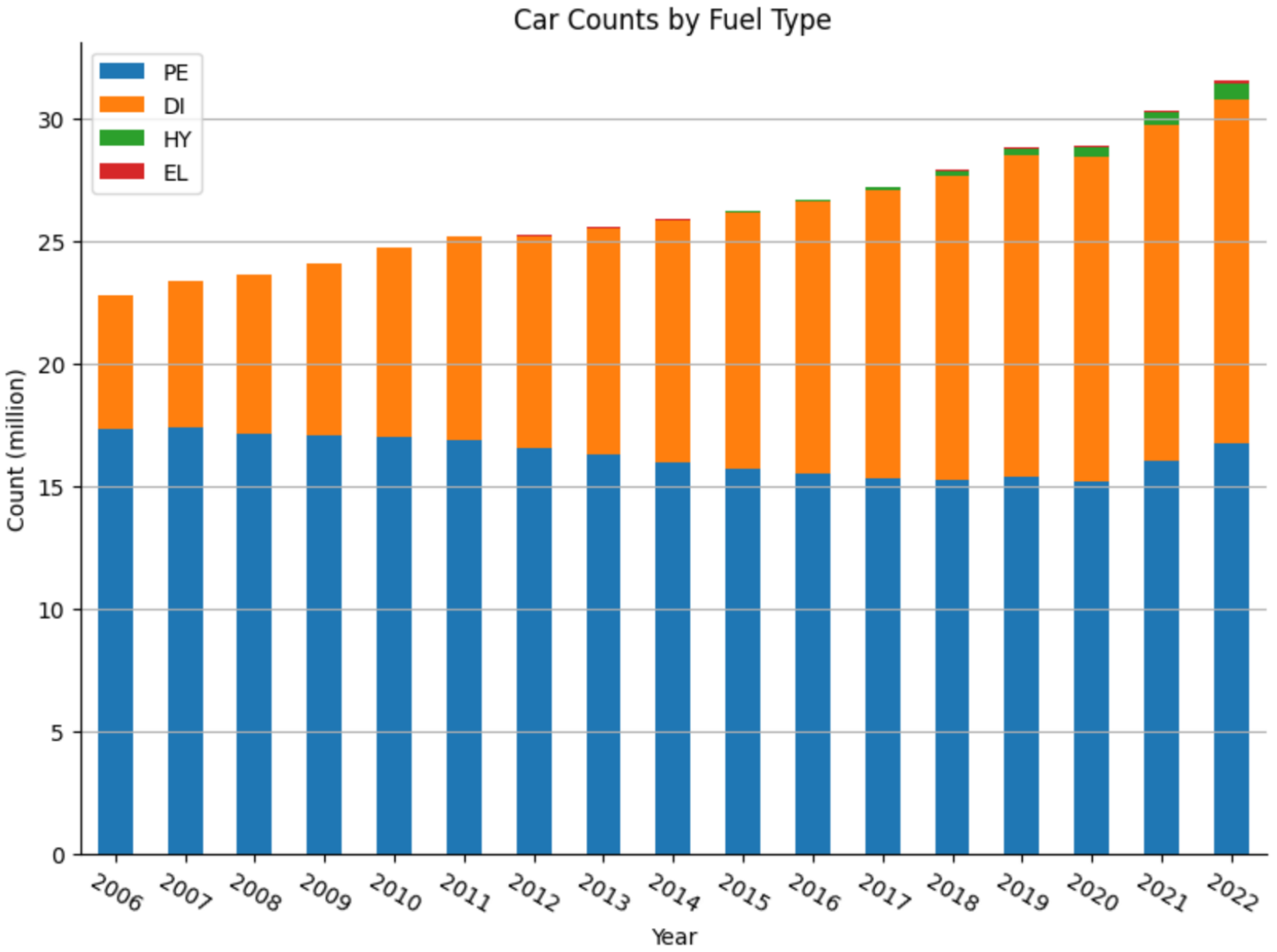
April drop **was due** to lockdown



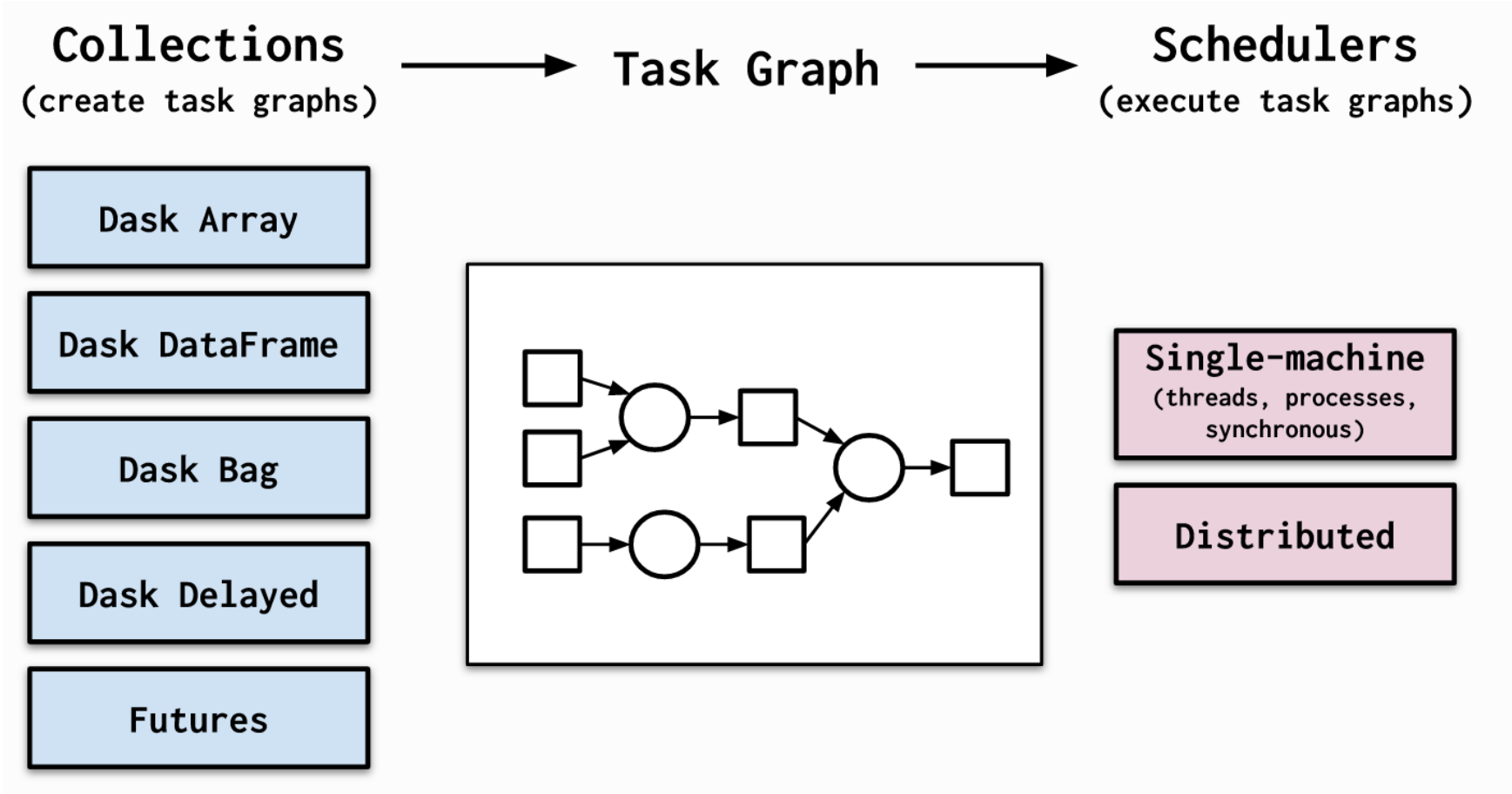
Vehicle ownership **increases**, Hybrids growing

We have to touch all parquet files, so we can’t easily use Pandas

MOT after 3 years of age for all vehicles



Dask scales Pandas (and lots more)



Dask

Original author(s)	Matthew Rocklin
Developer(s)	Dask
Initial release	January 8, 2015; 8 years ago
Stable release	2022.05.02 / May 2, 2022; 12 months ago


```
fuel_type_ddf = (
    dd.read_parquet(parquet_path, dtype_backend="pyarrow")
    .query('test_result == "P"')
    .replace({"fuel_type": {"Hybrid Electric (Clean)": "HY",
                            "Electric": "EL"}})
    .assign(Year=lambda x: x.test_date.dt.year)
    .groupby(["Year", "fuel_type"])
    .agg({"test_result": "count"})
    .rename(columns={"test_result": "vehicle_count"})
    .compute()
)
```

Last executed in 42.73s

```
ddf = dx.read_parquet(parquet_path, dtype_backend="pyarrow",)
fuel_type_ddf = (
    ddf[(ddf['test_result'] == "P")]
    #.query('test_result == "P"') # not in dask-expr 0.2.4
    .replace({"fuel_type": {"Hybrid Electric (Clean)": "HY",
                            "Electric": "EL"}})
    .assign(Year=lambda x: x.test_date.dt.year)
    .groupby(["Year", "fuel_type"])
    .agg({"test_result": "count"})
    .rename(columns={"test_result": "vehicle_count"})
    .optimize()
    .compute()
)
```

Last executed in 26.61s

"Basic" Dask, looks similar to Pandas
But lacks a query planner, so does unnecessary work

Dask Expressions only 6 months old, builds on existing DDF, undergoing rapid improvement
This includes a query planner

dask

polars

```
fuel_type_ldf.show_graph()
```



```python
fuel_type_ddf = (
    dd.read_parquet(parquet_path,
                    dtype_backend="pyarrow",
                    columns=["test_result", "test_date", "fuel_type"],
                    filters=[("test_result", "==", "P")],
    )
    .replace({"fuel_type": {"Hybrid Electric (Clean)": "HY",
                            "Electric": "EL"}})
    .assign(Year=lambda x: x.test_date.dt.year)
    .groupby(["Year", "fuel_type"])
    .agg({"test_result": "count"})
    .rename(columns={"test_result": "vehicle_count"})
    .compute()
)
```

```
Last executed in 23.26s
```

```python
fuel_type_edf = (
    pl.scan_parquet(parquet_path)
    .filter(pl.col("test_result") == "P")
    .with_columns(
        pl.col("fuel_type")
        .replace({"Hybrid Electric (Clean)": "HY", "Electric": "EL"},
                 default=pl.first())
        .cast(str),
        pl.col("test_date").dt.year().alias("Year"),
    )
    .group_by(["Year", "fuel_type"])
    .agg(pl.col("test_result").count().alias("vehicle_count"))
    .collect(streaming=True) # streaming required to prevent OOM
)
```

```
Last executed in 24.08s
```

Manual “Predicate & Projection Pushdown” to Parquet reader improves performance (but Expressions should do as well as this)

Dask faster in last 6 months too

Streaming allows bigger-than-RAM, still early-stage, required on 32GB laptop for this example but not on 64GB laptop

Thoughts on our testing

- Haven't checked lots of things!
- Numba doesn't compile Arrow extension array
- **NaN / Missing behaviour different Polars/Pandas**
- **sklearn partial support** (sklearn assumes Pandas API)
  – Polars working on dataframe interchange protocol
- Arrow timeseries/str **different** to Pandas NumPy?

Pandas vs Polars conclusions

- Polars easy to use, Pandas we all know
- **Arrow in both is great** (fast+low RAM footprint)
- Differences in Polars API (day of week starts at 1 not 0, no `sample` on LazyDF (Dask has API differences))
- Clear Polars API design **makes thinking easier**

Medium-data conclusions

- Dask ddf and Polars **can perform similarly**
- **Dask learning curve harder**, especially for performance
- **Dask does a lot more** (e.g. Bag, ML, NumPy, clusters, **diagnostics**)

We won the “rally”! ££→Parkinsons

Next year - vehicle telematics?

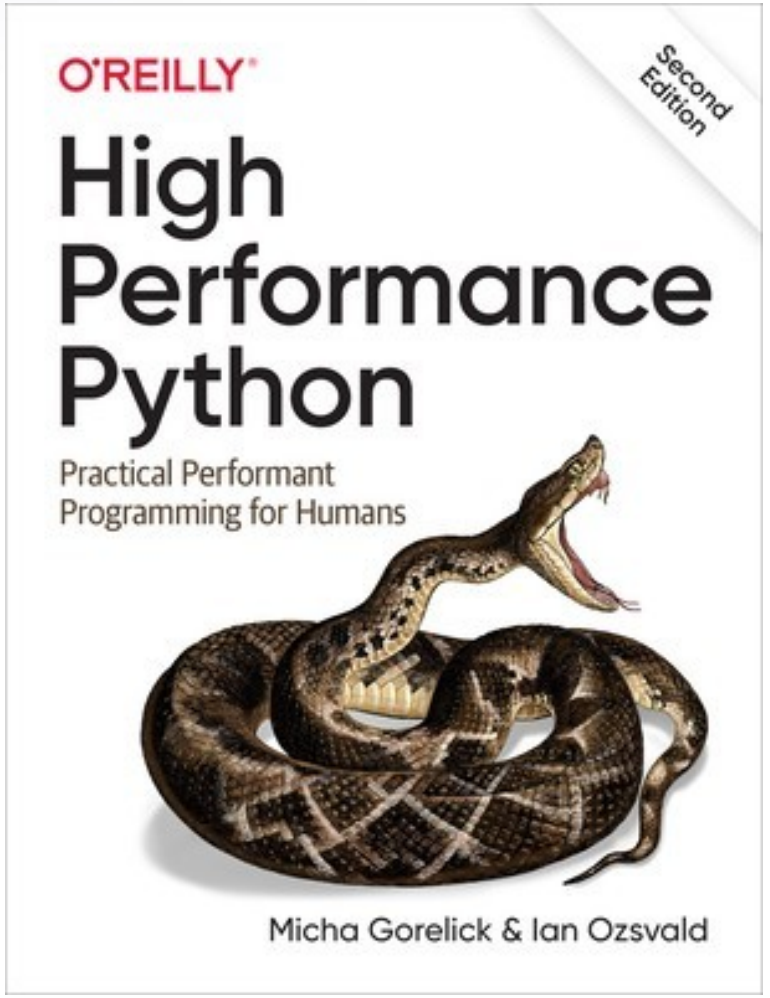
Summary

- Experiment, we have options!

NotANumber.email

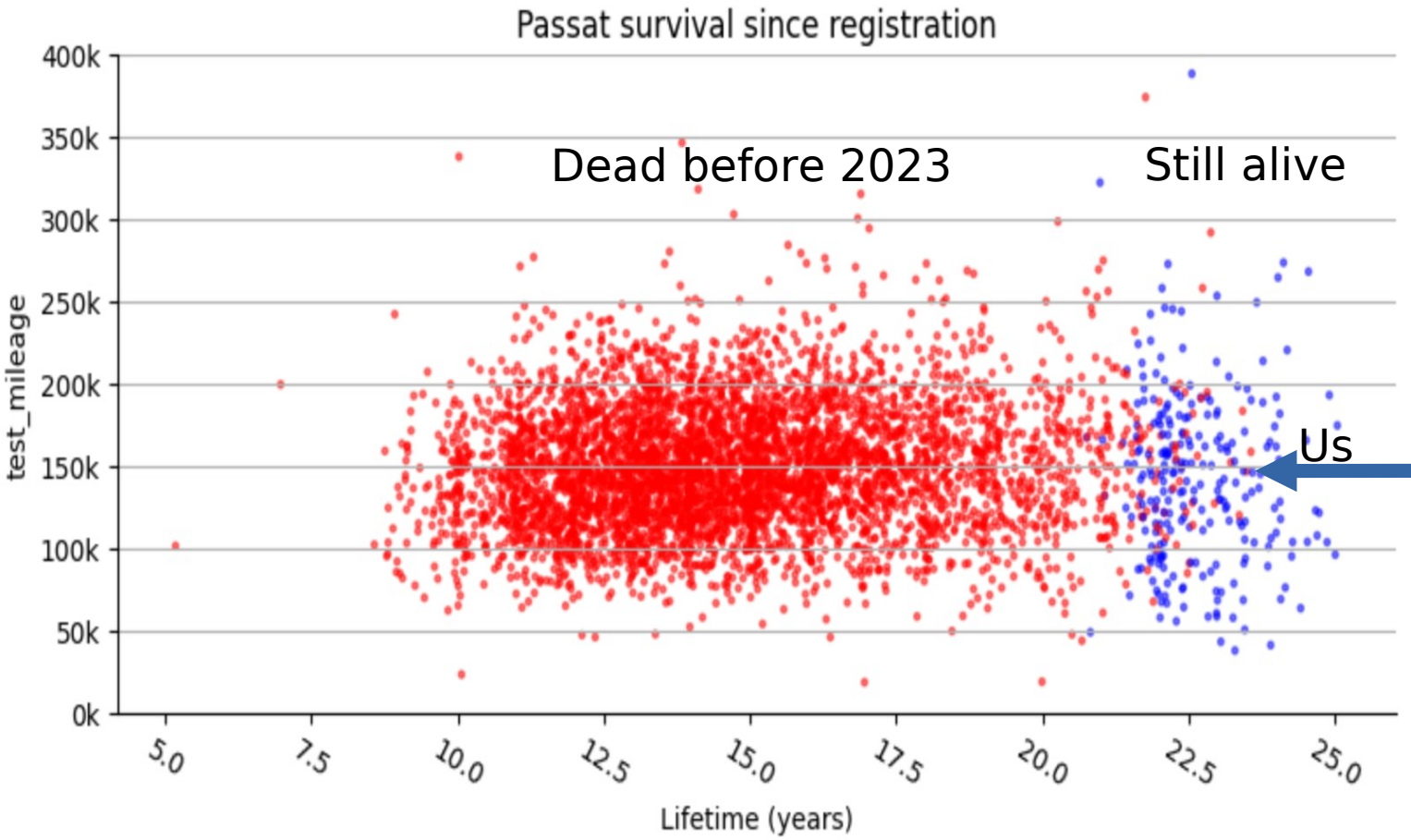
A Pythonic Data Science Newsletter

- **I love receiving postcards (email me)**



Appendix

For the rally we bought a ‘99 Passat



https://bit.ly/JustGivingIan

dask

Giles had to push directives to the Arrow read, set shuffle on set_index and agg

```
%%time
vehicle_summary_df = (
    dd.read_parquet(
        path="test_result.parquet",
        dtype_backend="pyarrow",
        columns=['vehicle_id', 'make', 'model', 'fuel_type',
                 'cylinder_capacity', 'first_use_date',
                 'test_date', 'test_mileage'],
        filters=[
            ("make", "in", ["VOLVO", "VOLKSWAGEN"]),
            ("model", "in", ["V50", "PASSAT"]),
        ],
    )
    .set_index('vehicle_id', npartitions=96, shuffle='tasks')
    .groupby("vehicle_id")
    .agg({"make": "last", "model": "last", "fuel_type": "last",
          "cylinder_capacity": "last", "first_use_date": "last",
          "test_date": "max", "test_mileage": "max"}, shuffle='tasks')
    .compute()
)
```

```
CPU times: user 8.46 s, sys: 1.5 s, total: 9.96 s
Wall time: 1min 6s
```

polars

```
%%time
edf = (
    pl.scan_parquet("test_result.parquet/*")
    .filter(pl.col("make").is_in(["VOLVO", "VOLKSWAGEN"]))
    .filter(pl.col("model").is_in(["V50", "PASSAT"]))
    .groupby("vehicle_id")
    .agg(
        pl.col(
            "make", "model", "fuel_type", "cylinder_capacity", "first_use_date"
        ).last(),
        pl.col("test_date").max().alias("last_test_date"),
        pl.col("test_mileage").max().alias("last_known_mileage"),
    )
    .collect()
)
```

```
PARTITIONED DS: estimated cardinality: 0.9911628 exceeded the boundary: 0.4, ru
```

```
CPU times: user 1min 51s, sys: 12.9 s, total: 2min 4s
Wall time: 11.7 s
```

3min+ with default 4 workers (*4 threads)

1min with 12 workers (*1 thr.) hand tuned

dask

Giles had to sort the Parquet (6 mins) & change groupby agg shuffle, else performance much worse

```
%%time
vehicle_summary_ddf = (
    dd.read_parquet(
        path="test_result_sorted.parquet",
        dtype_backend="pyarrow",
        index="vehicle_id",
        calculate_divisions=True,
    )
    .query(
        ('make in ["VOLVO", "VOLKSWAGEN", "ROVER"] & '
        'model in ["V50", "PASSAT", "200", "200 VI"]')
    )
    .dropna()
    .pipe(vehicle_grouper, groupby_sort=True, agg_shuffle="p2p")
    .compute()
)
```

```
CPU times: user 8.52 s, sys: 2.43 s, total: 11 s
Wall time: 1min 7s
```

3min+ with default 4 workers (*4 threads)
1min with 12 works (*1 thread) – hand tuned

polars

```
%%time
ldf = (
    pl.scan_parquet("../../test_result.parquet/*")
    .filter(pl.col("make").is_in(["VOLVO", "ROVER", "VOLKSWAGEN"]))
    .filter(pl.col("model").is_in(["V50", "200", "PASSAT"]))
    .groupby("vehicle_id")
    .agg(
        pl.col(
            "make", "model", "fuel_type", "cylinder_capacity", "first_use_date"
        ).last(),
        pl.col("test_date").max().alias("last_test_date"),
        pl.col("test_mileage").max().alias("last_known_mileage"),
    )
    .collect(streaming=True)
)
```

```
PARTITIONED DS: estimated cardinality: 0.9952009 exceeded the boundary: 0.4, run
CPU times: user 2min 20s, sys: 38.6 s, total: 2min 58s
Wall time: 16.8 s
```

Manual Query Planning

```
%time dfpda.query('test_result=="P"');
```

```
CPU times: user 6.63 s, sys: 4.31 s, to
Wall time: 10.9 s
In [23] used 0.0 MiB RAM in 11.13s (sys
ingle max cpu 100%), peaked 9534.4 MiB
```

```
%%time
cols = ["test_mileage", "fuel_type",
        "first_use_date"]
dfpda[pass_mask][cols];
# select all columns after mask
```

```
CPU times: user 5.88 s, sys: 4.29 s, t
Wall time: 10.1 s
In [26] used 0.0 MiB RAM in 10.27s (sy
ingle max cpu 100%), peaked 9178.8 MiB
```

```
%%time
pass_mask = dfpda["test_result"] == "P";
# make mask only
```

```
CPU times: user 391 ms, sys: 4.77 ms, to
Wall time: 394 ms
In [47] used 0.0 MiB RAM in 0.49s (syste
ngle max cpu 100%), peaked 19.3 MiB abov
```

```
%time dfpda[cols][pass_mask];
# select all columns before mask
```

```
CPU times: user 1.48 s, sys: 870 ms,
Wall time: 2.34 s
In [27] used 0.0 MiB RAM in 2.48s (sy
ngle max cpu 100%), peaked 2498.2 MiB
```