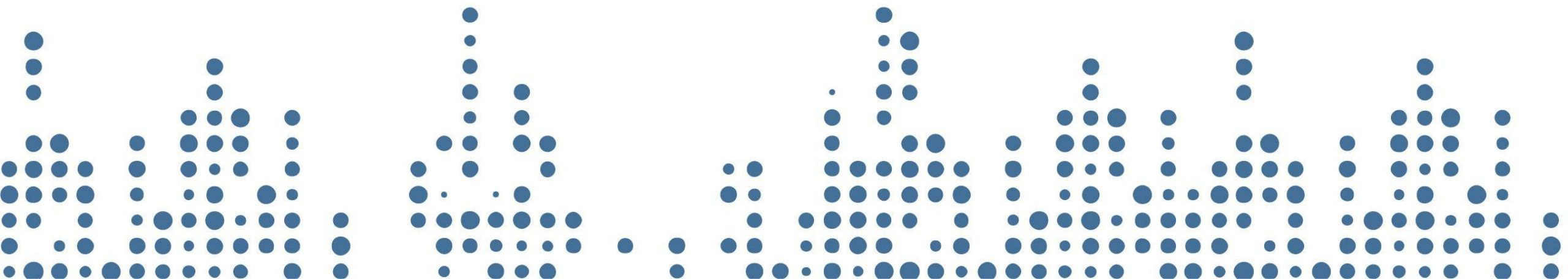




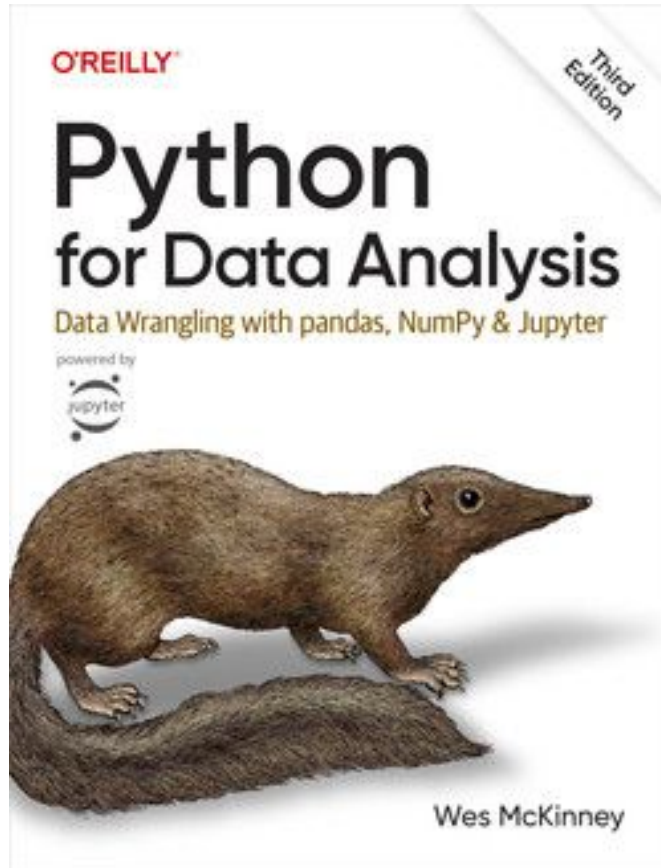
# Brief Overview of My Path to Composable Data Systems

Wes McKinney  
June 2024





Me



Ibis





Me

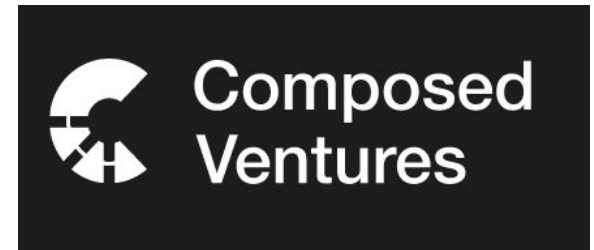


**Principal  
Architect**



VOLTRON DATA

**Co-founder,  
Advisor**



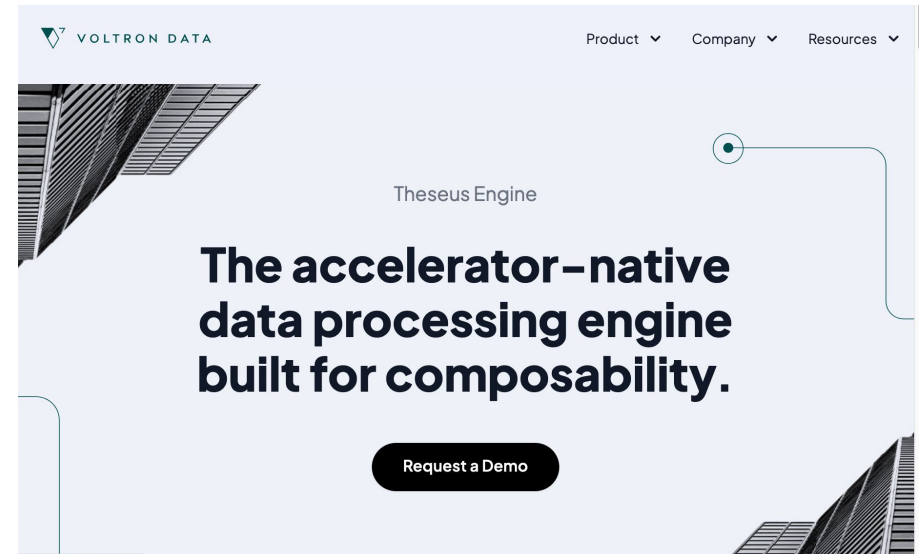
**General Partner**





## Voltron Data (2021 — )

- Unlocking the potential of GPU accelerated analytics for large scale workloads
- Enterprise support for Apache Arrow and Ibis
- Open source partnerships (Meta, Snowflake, others)
- \$115M raised, 130 headcount and growing





## Posit PBC

- Founded 2009, originally as RStudio
- ~300 person, remote-first company
- Open source software for code-first data science and technical communication
- Certified B corp, no plans to go public or be acquired
- Designing for long-term resiliency, creating a 100-year company





## Brief History of pandas



- Development started in 2008 at AQR, a quant hedge fund
- Open sourced late 2009
- ***Python for Data Analysis, 1e*** published in August 2012
- Became a community-owned open source project in 2013





## pandas in the Python data stack

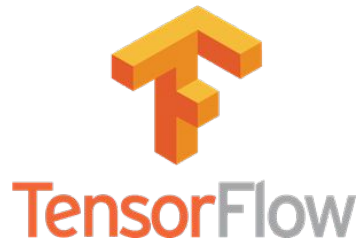


- Essential data access (CSV, SQL, etc.) and in-memory data structures
- Data cleaning and manipulation
- Interactive / exploratory analysis
- First step in larger workflows before scikit-learn or other modeling libraries





How did Python become so popular?





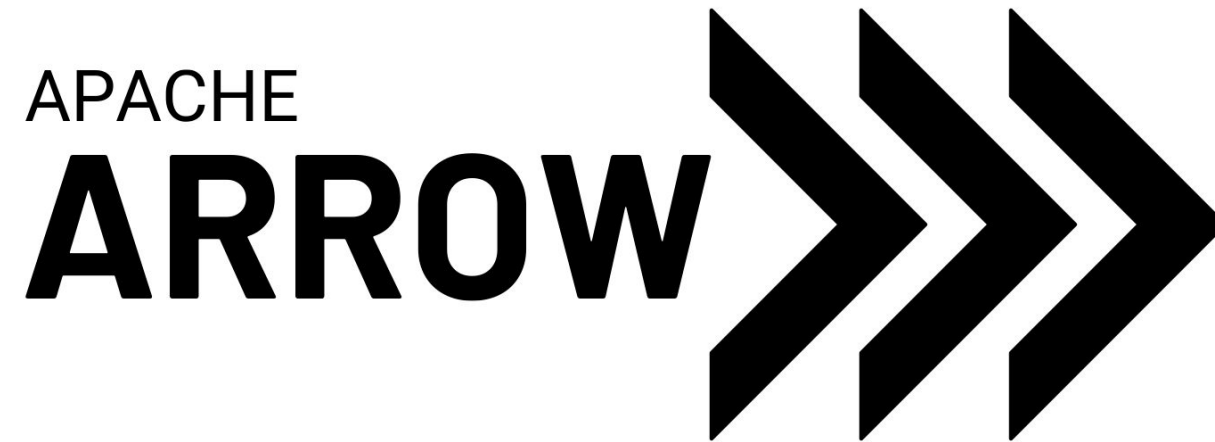


## Python and Big Data

- Initial wave of Big Data systems were Java/JVM centric
- Python support was largely an afterthought
- Circa 2014: difficult for R/Python to access data originating in the Hadoop ecosystem



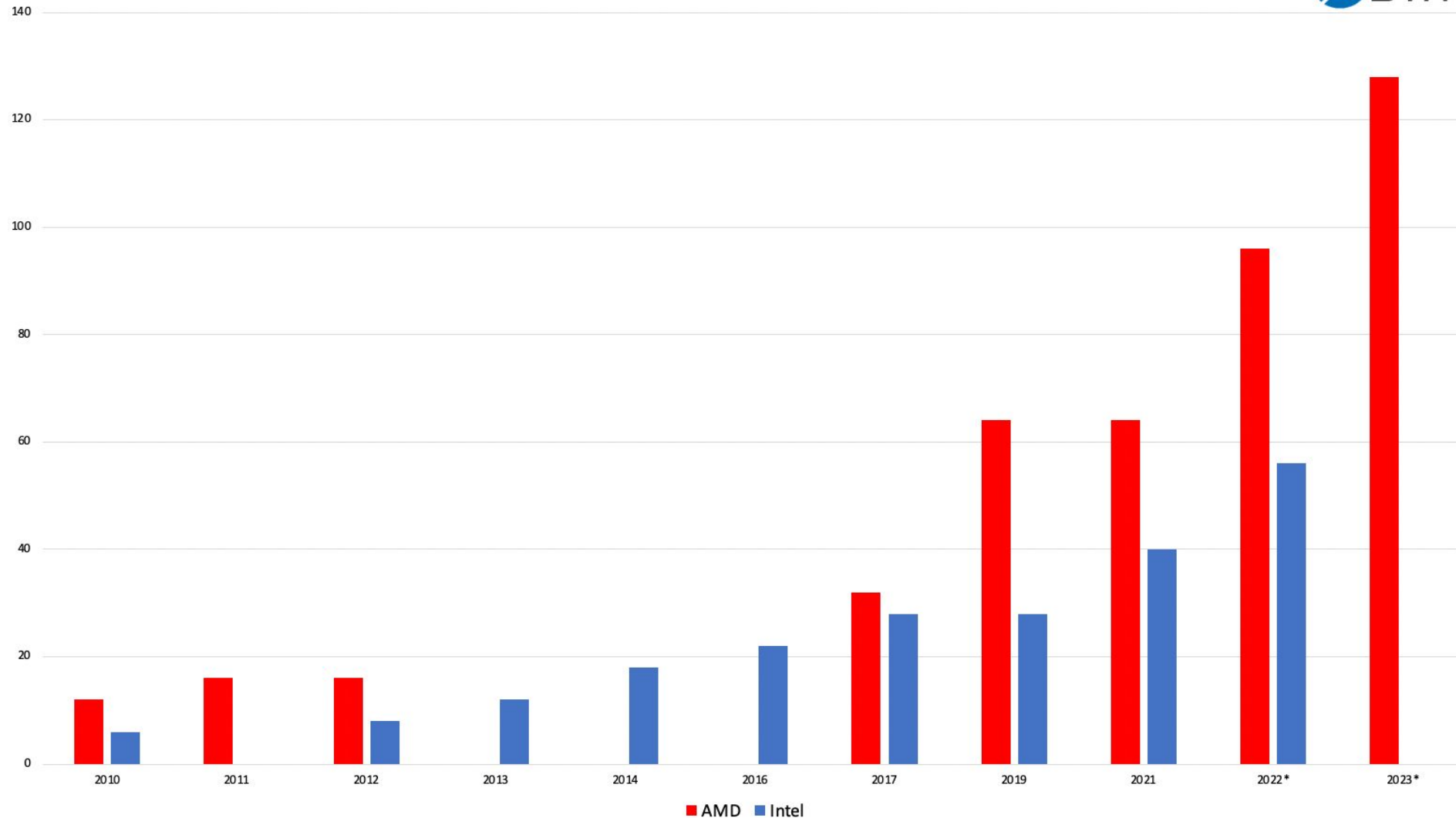
# 2016: A Cross-Language Fast In-Memory Data Format



**How has computing  
hardware changed over the  
last 20 years?**

## Intel and AMD Core Count Growth 2010-2022 Plus "Bergamo" (Estimated)

Maximum Per Socket Core Count in Mainstream 2-Socket Server by Release Year



<https://www.servethehome.com/amd-and-intel-2p-server-core-count-growth-2010-2022/>

# AMD EPYC™ 9654

**Regional Availability:** Global,  
China, NA, EMEA, APJ, LATAM

**Platform:** Server

**Product Family:** AMD EPYC™

**Product Line:** AMD EPYC™ 9004  
Series

**# of CPU Cores:** 96

**# of Threads:** 192

**Max. Boost Clock**: Up to  
3.7GHz

**All Core Boost Speed**: 3.55GHz

**Base Clock:** 2.4GHz

**L3 Cache:** 384MB

**1kU Pricing:** 11,805 USD

**Default TDP:** 360W

**AMD Configurable TDP (cTDP):**  
320-400W

**CPU Socket:** SP5

**Socket Count:** 1P / 2P

**Launch Date:** 11/10/2022

# Trends in Disk Performance

<b>Speed Statistic</b>	<b>HDD (Hard Disk Drive)</b>	<b>SSD (Solid State Drive)</b>	<b>NVMe m.2 (Nonvolatile Memory Express)</b>
<b>Read Speed</b>	80 MB/s	200MB/s	5000 to 7300 MB/s
<b>Write Speed</b>	160 MB/s	550 MB/s	5000 to 6350 MB/s
<b>Capacity Available</b>	From 250GB to 14TB	250GB to 4TB	500GB to 4TB

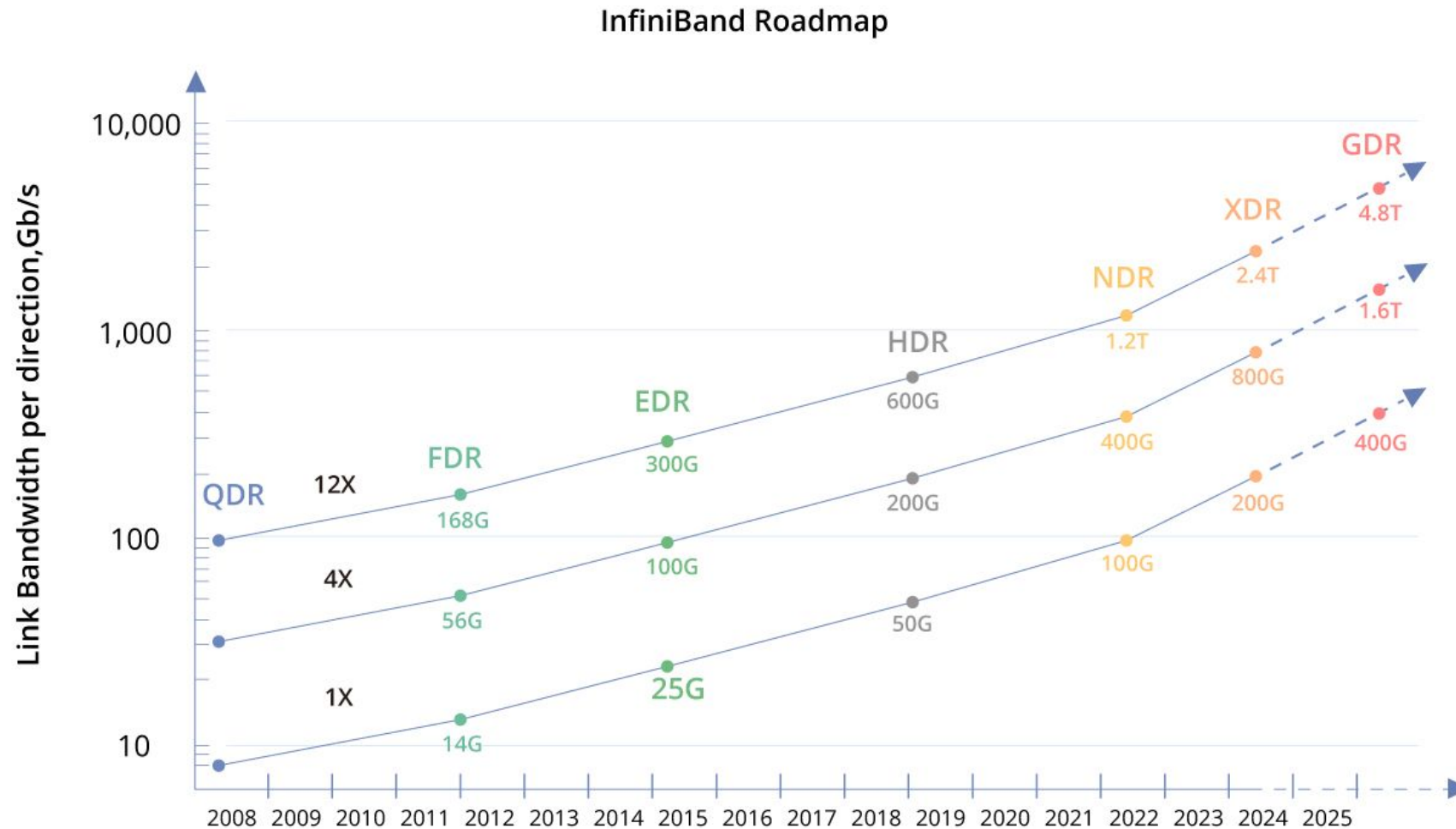
Seeks

**~10ms**

**~0.1ms**

**~0.1ms**

# Trends in Networking Performance



# Python

```
import pandas as pd

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

df2 = pd.read_sql("select * from db.flights", con)

result = (
    df2.mutate(dep_minutes=df2['dep_delay'] / 60)
    .groupby('orig_code')
    ['dep_delay'].mean()
)
```



R

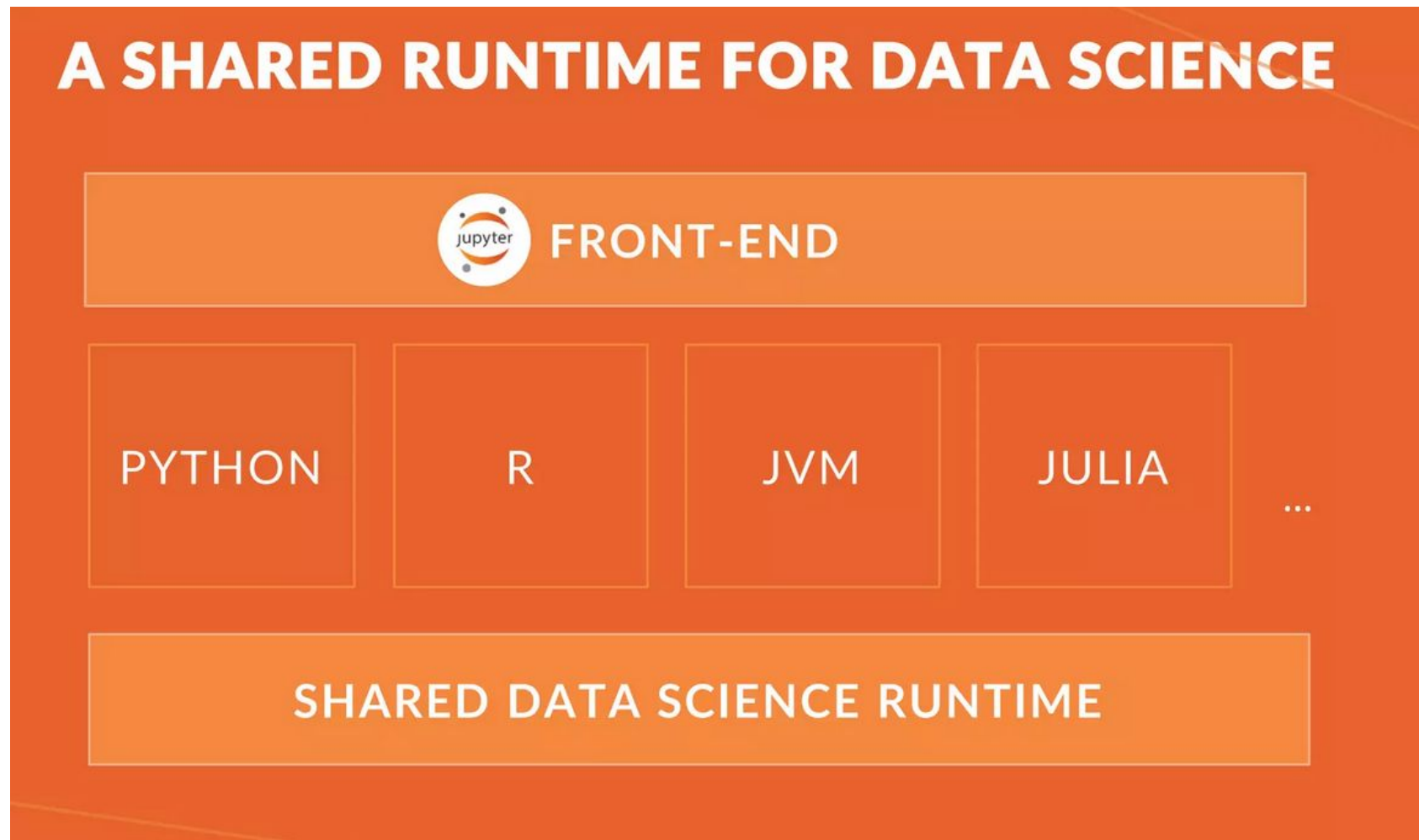
```
flights <- read_csv('flights.csv')

flights %>%
  mutate(dep_minutes=dep_delay / 60) %>%
  group_by("orig_code") %>%
  aggregate(avg_delay=mean(dep_delay))
```

# SQL

```
SELECT orig_code, avg(dep_delay) as avg_delay  
FROM flights  
GROUP BY 1
```

# Mid-2010s Vision



<https://www.slideshare.net/wesm/data-science-without-borders-jupytercon-2017>



Apache Arrow Development Group

## Sponsors



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## Why now?

- 1st-Gen Big Data / Hadoop Era: 2006 - 2013
  - MapReduce popularizes disaggregated storage + compute
- 2nd-Gen 2013 - 2021
  - Vendors shift from proprietary software to delivery of services
  - Open source standards emerge and are popularized
  - Rapid progress in storage, networking, computing performance
- 3rd-Gen 2021 - ... ?
  - Open standards for composability become widely accepted
  - Next-gen components emerge, existing systems start retrofitting with composable pieces





## Data Lake Access



## Data Lake Access



## Language Interoperability





## Data Lake Access



## Fast Embeddable Execution



## Language Interoperability



## Data Lake Access



## Accelerated Database Connectivity

ADBC

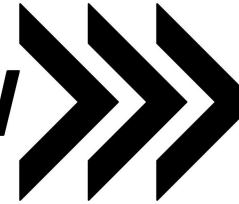


FlightSQL



APACHE

**ARROW**



## Fast Embeddable Execution



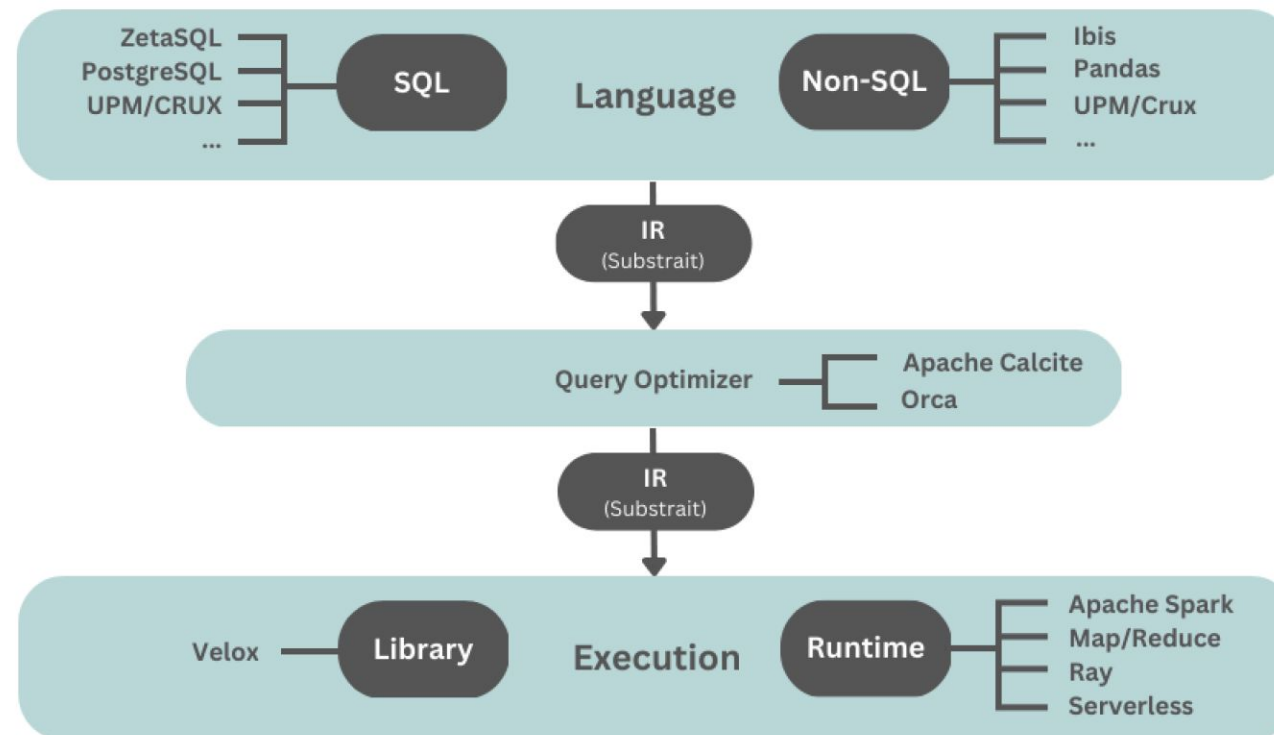
DuckDB



## Language Interoperability



## > Layers of the Composable Cake



**Figure 1: Open source modular data stack outline.**



## Modular Execution Engines

- Apache DataFusion (Rust)
- DuckDB (C++)
- Polars (Rust)
- Velox (C++)
- Theseus (C++ / CUDA)

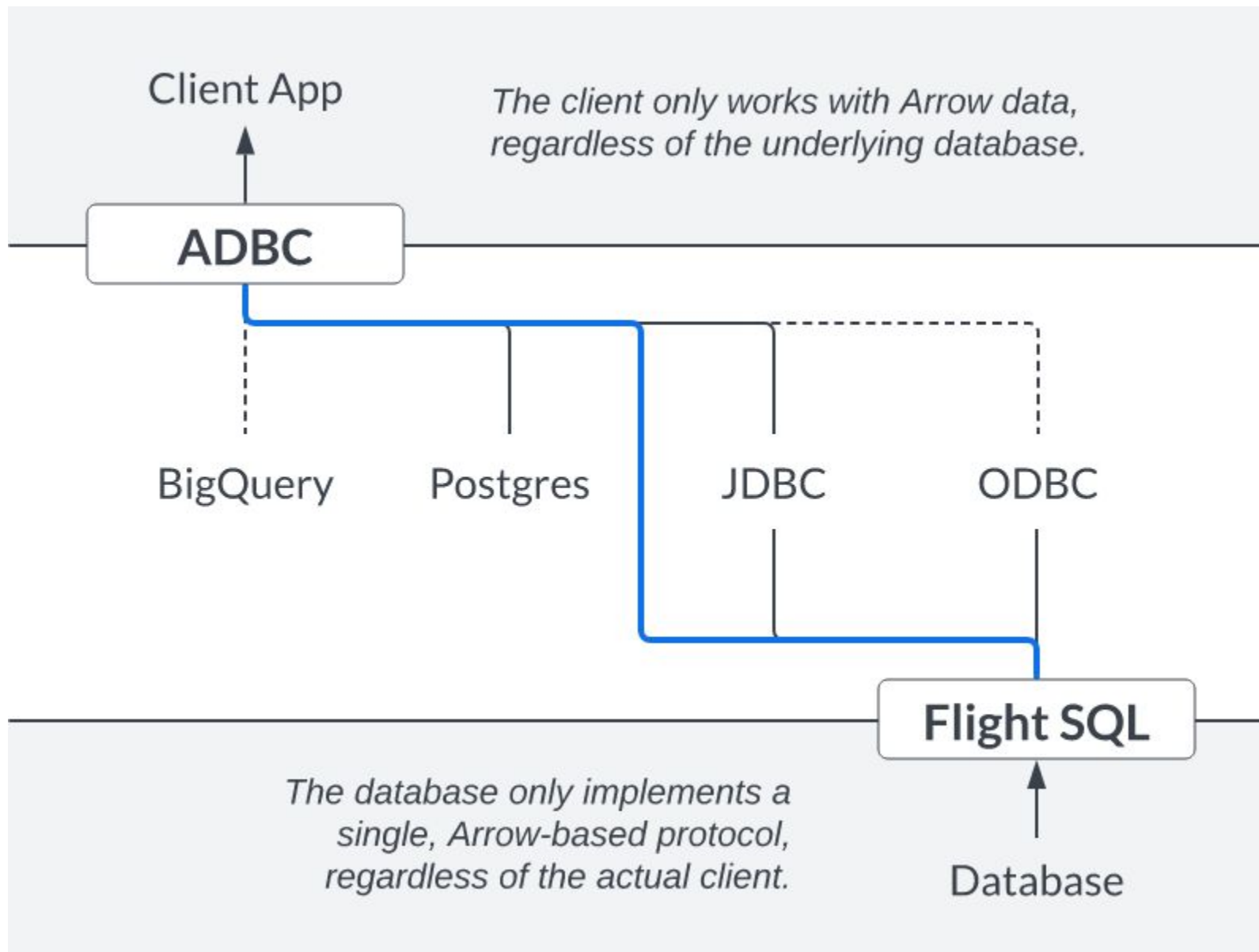




## Modular Acceleration Projects

- Prestissimo (Velox in Presto)
- Apache DataFusion Comet (DataFusion in Spark)
- Apache Gluten (incubating) (Velox in Spark)







## What is a “Composable Data System”?

- Builds with open standards and protocols
- Designed around modularity, reuse, and interoperability with other systems that use shared interfaces
- Resists “vertical integration”, builds in a virtual cycle with relevant open source ecosystem projects





## A Multi-Engine Data Stack?

- Why be locked into one full-stack execution engine (like Spark)?
- Cost/performance/latency varies greatly across workload shapes and sizes
- You can do a lot with DuckDB, but actual big data does still exist

HT to Julien Hurault ! <https://juhache.substack.com/p/multi-engine-data-stack-v0>







## Barriers to a multi-engine data stack

- SQL dialects are non-portable and feature a wide spectrum of supported features
  - sqlglot is helping with this!
- Deciding which engine-to-use is non-trivial
- Diverse orchestration and infrastructure requirements





Enter the Bird



**ibis-project.org**

- An effort to harmonize the best of modern SQL with Pythonic fluent data frames
- Fixing a long list of shortcomings in the pandas API
- Leverage the benefits of a modern PL when creating complex analytical SQL queries
- Bringing portability (> 20 backends supported) to provide a unified Python API for a multi-engine data stack



```
left = ents.filter(_.known_for_titles.length() > 0).limit(10_000)
right = left.view()
shared_titles = (
  left
  .join(right, left.nconst != right.nconst)
  .select(
    s.startswith("known_for_titles"),
    left_name="primary_name",
    right_name="primary_name_right",
  )
  .filter(_.known_for_titles.intersect(_.known_for_titles_right).length() > 0)
  .group_by(name="left_name")
  .agg(together_with=_.right_name.collect())
  .mutate(together_with=_.together_with.unique().sort())
)
shared_titles
```

<https://ibis-project.org/posts/bigquery-arrays/>



## A Future Multi-Engine Stack

- An execution engine tailored for different data scales
  - $\leq 1\text{TB}$ : DuckDB and Friends
  - 1 - 10TB: Spark, Dask, Ray, etc.
  - $> 10\text{TB}$ : GPU-accelerated Processing
- A portable language front end (Ibis, Malloy, PRQL, or a standard transpilable SQL)
- Arrow-native API and wire transport

