

# **Data Engineering Project**

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fastestLap rank fastestLapTime

# Design overview

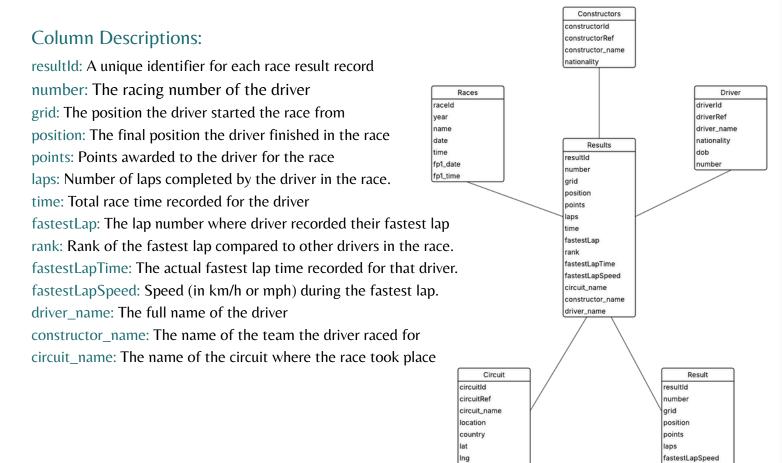
This project demonstrates an end-to-end data engineering pipeline using a Formula 1 race results dataset. The goal is to ingest, store, query, process, and visualize racing data from multiple angles using different storage and processing technologies.

#### **Dataset Description:**

The dataset used in this project is Formula 1 racing data, originally spread across five separate files containing details about drivers, constructors, circuits, and race results. To simplify processing and analysis, we merged these files into one unified dataset by combining important columns like driver\_name, constructor\_name, and circuit\_name. This combined dataset contains 26,760 rows and 15 columns, with each row representing a driver's performance in a specific race.

#### Denormalization:

We decided to use denormalization because it was more useful for our project than normalization. Instead of keeping many separate tables, we combined all the important data like driver names, constructors, and circuit details into one big table called Results. This made it easier and faster to get the information we needed without doing many complicated joins between tables, which made working with the data more quickly and simply.







# Design overview

### Phase One:

First we designed a denormalized schema by using SQLite for implementation. We created the Results table by joining relevant attributes from drivers, constructors, and circuits, perform CRUD operations, and applied indexing and basic optimization (INDEX ON driver\_name) to improve query speed.

#### example of CRUD operations

```
conn = sqlite3.connect("F1.db")
cursor = conn.cursor()

cursor.execute("""
SELECT driver_name, SUM(points) AS total_points
FROM Results
GROUP BY driver_name
ORDER BY total_points DESC
LIMIT 5
""")

top_drivers = cursor.fetchall()
print("Top 5 Drivers by Total Points:")
for driver in top_drivers:
    print(f"Driver Name: {driver[0]}, Total Points: {driver[1]}"

Top 5 Drivers by Total Points:
Driver Name: Lewis Hamilton, Total Points: 4845.5
Driver Name: Sebastian Vettel, Total Points: 3098.0
Driver Name: Max Verstappen, Total Points: 2912.5
Driver Name: Fernando Alonso, Total Points: 2929.0
Driver Name: Kimi Räikkönen, Total Points: 1873.0
```

#### indexing and query optimization

```
df = pd.read_sql_query(query, conn)
print("Time without index:", time.time() - start)
     SELECT driver_name, COUNT(*) AS races_participated
    FROM Results
                                                                     cursor.execute("CREATE INDEX IF NOT EXISTS idx_driver_name ON Results(driver_name)")
    ORDER BY races_participated DESC
LIMIT 10
    df = pd.read_sql_query(query, conn)
Ŧ
               driver_name races_participated
           Fernando Alonso
                              404
    2
           Kimi Räikkönen
                                            352
         Rubens Barrichello
                                            326
     5 Michael Schumacher
                                             308
           Sebastian Vettel
    6
                                            300
          Felipe Massa
                                            271
           Riccardo Patrese
```

## Phase Two:

In this phase, we explored NoSQL data handling by storing and interacting with a subset of the Formula 1 dataset in a document-based format using TinyDB. The dataset was transformed into a JSON-like structure and inserted into the database.

We carried out all the fundamental NoSQL tasks: inserting new records, query optimization, aggregating data to highlight top performers, updating selected fields, and deleting individual records

```
from tinydb import TinyDB, Query

from google.colab import files
uploaded = files.upload()

F1_results.csv
F1_results.csv
F1_results.csv(ext/csv) - 229826 bytes, last modified: 12100%
Saving F1_results.csv to F1_results.csv

[4] import pandas as pd

df = pd.read_csv('F1_results.csv')
subset_df = df.head(1000)

[5] data = subset_df.to_dict(orient='records')

from tinydb import TinyDB

db = TinyDB('f1_results.json')

db.insert_multiple(data)
print("Subset inserted into TinyDB")

Subset inserted into TinyDB
```

```
Result = Query()

drivers = db.search(Result.constructor_name == 'McLaren'
unique_driver_names = set()

for r in drivers:
    unique_driver_names.add(r['driver_name'])
    print("Drivers from McLaren:\n")
    for name in sorted(unique_driver_names):
        print(name)

Drivers from McLaren:

Fernando Alonso
    Heikki Kovalainen
    Juan Pablo Montoya
    Kimi Räikkönen
    Lewis Hamilton
    Pedro de la Rosa
```

```
from collections import Counter
winners = [r['driver_name'] for r in db.search(Result.
position == '1')]
top_winners = Counter(winners).most_common(5)
print("Top 5 Drivers with Most Wins:\n")
for name, wins in top_winners:
    print(f"(name): {wins} wins")

Top 5 Drivers with Most Wins:
Fernando Alonso: 36 wins
Lewis Hamilton: 27 wins
Felipe Massa: 27 wins
Kimi Räikkönen: 24 wins
Michael Schumacher: 15 wins
```





# Design overview

## Phase Three:

We simulated a live data stream by reading the f1\_subset\_results.csv file, which was a result of phase2 and contained preprocessed and merged race data from various sources, including driver, constructor, and circuit information.

Using PySpark, we applied filtering operations to retain only those records where drivers scored more than 10 or 18 points, allowing us to identify high performing participants across different races.

11 630	ıltId nu	mber g	grid posi	tion p	oints	laps  tim	e fastestLap	rank 1	fastestLapTime	fastestLapSpeed	driver_name	constructor_name	circuit_name	
1	1	22  3  7  23	1	1	10.0	58 1:34:50.61	5 39	2	1:27.452	218.300	Lewis Hamilton	McLaren	Albert Park Grand	
İ	2	3	5	2	8.0	58 +5.47	8 41	3	1:27.739	217.586	Nick Heidfeld	BMW Sauber	Albert Park Grand	
ĺ	3	7	7	3	6.0	58 +8.16	3 41	5	1:28.090	216.719	Nico Rosberg	Williams	Albert Park Grand	
i	5	23	3	5	4.0	58 +18.01	4 43	1	1:27.418	218.385	Heikki Kovalainen	McLaren	Albert Park Grand	
i	6		13	6	3.0	57  \	N 50		1:29.639	212.974	Kazuki Nakajima		Albert Park Grand	
+	+	+-	+	+-	+-		-+	+	+		+			
res			grid posi			laps  tim	e fastestLap	rank	fastestLapTime	fastestLapSpeed	driver_name cor	nstructor_name	circuit_name	
i					-	58 1:34:56.78	9 42	1	1:31.456	228.3	Lewis Hamilton	McLaren   Yas	s Marina Circuit	
							-4				A			

## Phase Four:

We built the dashboard in a structured project folder and imported race results data from the F1\_results.csv file using a dedicated Python script. The data was loaded into a SQLite database and displayed interactively through the dashboard interface. The dashboard provided dynamic updates, allowing any changes in the underlying data to be reflected in real time upon refresh







# Top 5 Drivers by Points Driver Name Total Points Lewis Hamilton 4845.5 Sebastian Vettel 3098 Max Verstappen 2912.5 Fernando Alonso 2329 Kimi Räikkönen 1873









## **Lessons Learned**

- Combining datasets early improves consistency and reduces redundancy
- While denormalization and indexing can speed up queries in SQLite, they require thoughtful planning to manage data duplication and maintain consistency
- NoSQL databases like TinyDB are ideal for flexible, nested data structures
- PySpark requires clean and schema-consistent JSON files for efficient processing
- Each technology has strengths; integration teaches adaptability across storage paradigms
- Visualization tools make insights more accessible and highlight the importance of data quality
- Organizing code and files clearly makes the project easier to manage
- Working with a team improved our communication, time management, and problem-solving skills
- Data engineering is not just about storing data, it's making it ready for analysis, automation, and insights.
- Realizing how data engineers play a key role in turning data into value for companies and users