

Project Objective And Scope



Analyze Flight Delays & Performance

- Identify patterns and trends in flight delays, on-time performance across airlines and airports.
- Understand the impact of taxi-in, taxi-out, and cancellations on overall flight schedules.



Optimize Airline & Airport
Operations

- Provide insights to improve scheduling, reduce delays, and enhance ground operations.
- Help airlines and airports better manage resources based on delay trends and seasonal flight performance.



Enhance Passenger Experience & Reliability

- Help passengers make informed travel decisions.
- Improve customer satisfaction by reducing unexpected travel disruptions.

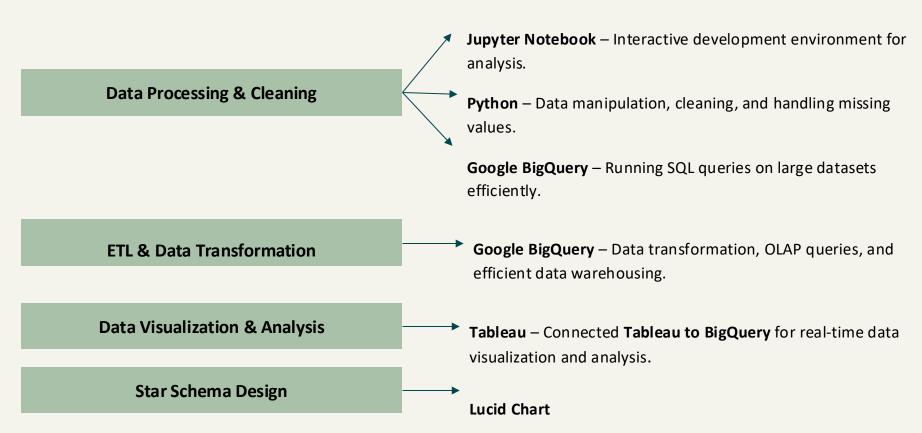
Goal Of The Project Market

The final goal of this project is to provide a comprehensive analysis of flight's operational efficiency by utilizing OLAP queries to extract meaningful insights and cost management

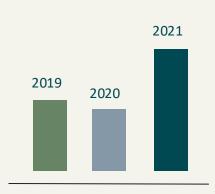
- Understand factors causing delays and cancellations.
- Identify patterns in delays based on various aligned factors.
- Airline and airport performance benchmarking.



Software Implementation



Data & Data Source



Data Source: Kaggle

Data Span: 3 years

Flight data: 19 million rows and 61 columns

Data Type: Parquet format

FlightDate	datetime64[ns]
Airline	category
Flight_Number_Marketing_Airline	int64
Origin	category
Dest	category
Cancelled	bool
Diverted	bool
CRSDepTime	int64
DepTime	float64
DepDelayMinutes	float64
OriginAirportID	int64
OriginCityName	object
OriginStateName	category
DestAirportID	int64
DestCityName	object
DestStateName	category
TaxiOut	float64
TaxiIn	float64
CRSArrTime	int64
ArrTime	float64
ArrDelayMinutes	float64
AirTime	float64
CRSElapsedTime	float64
ActualElapsedTime	float64
Distance	float64
Day0fWeek	int64
DepDel15	float64
ArrDel15	float64
DepartureDelayGroups	float64
ArrivalDelayGroups	float64
dtype: object	

Data Warehouse Design Overview

Data Warehouse: Google BigQuery

Schema Type: Star Schema

Query Language : BigQuery SQL

BI Tool : Tableau



ETL











EXTRACTION

Data Source

 Flight records in Parquet format from Kaggle.

TRANSFORMATIONS

Data Cleaning & Standardization

- Removed duplicate records.
- Handle Outliers
- Handled missing values (e.g., filling with defaults or removing incomplete rows).
- Standardized date & time formats (converted timestamps to a uniform format).

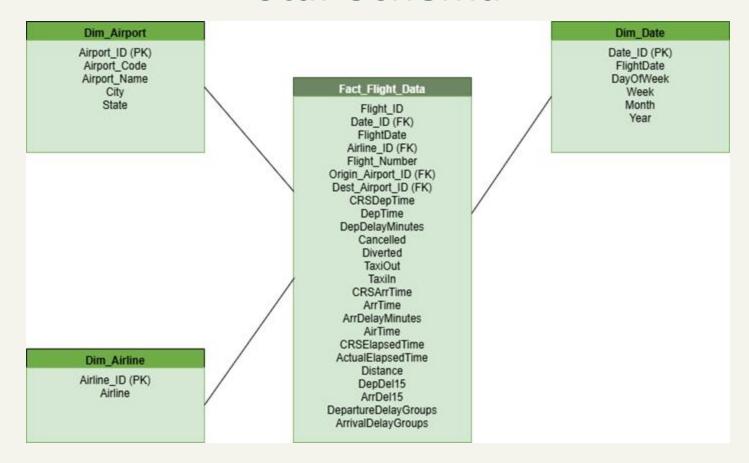
LOADING

Schema Design

Transformed data was loaded into Google BigQuery.

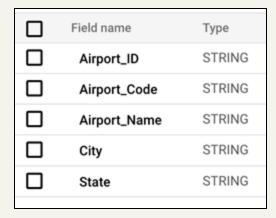
- Created Fact Table and Dimension Tables:
- Aggregate data for OLAP operations.
- Join fact and dimension tables.

Star Schema



Fact & Dimension Table

dim_airport



dim_date

Field name	Туре
Date_ID	STRING
FlightDate	DATE
DayOfWeek	INTEGER
Week	INTEGER
Month	INTEGER
Year	INTEGER

dim_airline

Field name	Туре
Airline_ID	INTEGER
Airline	STRING

Fact Table

Field name	Туре
Flight_ID	STRING
Date_ID	STRING
FlightDate	DATE
Airline_ID	INTEGER
Flight_Number_Marketing_Airline	STRING
Origin_Airport_ID	STRING
Dest_Airport_ID	STRING
CRSDepTime	INTEGER
DepTime	INTEGER
DepDelayMinutes	INTEGER
Cancelled	INTEGER
Diverted	INTEGER
TaxiOut	INTEGER
Taxiln	INTEGER
CRSArrTime	INTEGER
ArrTime	INTEGER
ArrDelayMinutes	INTEGER
AirTime	INTEGER
CRSElapsedTime	INTEGER
ActualElapsedTime	INTEGER
Distance	FLOAT
DepDel15	INTEGER
ArrDel15	INTEGER
DepartureDelayGroups	INTEGER
ArrivalDelayGroups	INTEGER

Incremental Update of DW

Monthly Update

- New flight records for the latest month (Fact Table)
- New airlines, airports, and dates (Dimension Tables)

Steps

Extracting new or modified records from the source system.

- Comparing against existing data in DW.
- Inserting new records and update existing ones.
- Automating it using Python (ETL),SQL.

Scripts of The Incremental Update

```
INSERT INTO bamboo-medium-450316-m8.flight data.fact flight data (
   Flight ID, Date ID, Airline ID, Origin Airport ID, Dest Airport ID,
   DepDelayMinutes, ArrDelayMinutes, Cancelled, FlightDate, LastUpdated
SELECT
   source.Flight ID, source.Date ID, source.Airline ID,
   source.Origin Airport ID, source.Dest Airport ID,
   source.DepDelayMinutes, source.ArrDelayMinutes,
   source.Cancelled, source.FlightDate, CURRENT TIMESTAMP
FROM bamboo-medium-450316-m8.flight data.staging fact flight data AS source
WHERE EXTRACT(YEAR FROM source.flightDate) = EXTRACT(YEAR FROM CURRENT DATE())
  AND EXTRACT(MONTH FROM source.FlightDate) = EXTRACT(MONTH FROM CURRENT DATE())
ON DUPLICATE KEY UPDATE
   DepDelayMinutes = VALUES(DepDelayMinutes),
   ArrDelayMinutes = VALUES(ArrDelayMinutes),
   Cancelled = VALUES(Cancelled),
   LastUpdated = CURRENT TIMESTAMP;
```

```
INSERT INTO dim_date (Date_ID, FlightDate, Year, Month, DayOfWeek)

SELECT DISTINCT

DATE_FORMAT(FlightDate, '%Y%n%d') AS Date_ID,
    FlightDate,
    YEAR(FlightDate),
    MONTH(FlightDate),
    DAYOFWEEK(FlightDate)

FROM staging_fact_flight_data
WHERE EXTRACT(YEAR FROM FlightDate) = EXTRACT(YEAR FROM CURRENT_DATE())
AND EXTRACT(MONTH FROM FlightDate) = EXTRACT(MONTH FROM CURRENT_DATE())
ON DUPLICATE KEY UPDATE
    Year = VALUES(Year),
    Month = VALUES(Month),
    DayOfWeek = VALUES(DayOfWeek);
```

```
INSERT INTO dim_airline (Airline_ID, Airline)

SELECT DISTINCT Airline_ID, Airline

FROM staging_fact_flight_data

ON DUPLICATE KEY UPDATE

Airline = VALUES(Airline);

INSERT INTO dim_airport (Airport_ID, Airport_Code, Airport_Name, City, State)

SELECT DISTINCT Origin_Airport_ID AS Airport_ID, Origin AS Airport_Code, OriginCityName AS Airport_Name, OriginStateName AS State

FROM staging_fact_flight_data

ON DUPLICATE KEY UPDATE

Airport_Code = VALUES(Airport_Code),
Airport_Name = VALUES(Airport_Name),
State = VALUES(State))
```

Business Intelligence

Er	nd Users	Use case
01	Executives	High-level reports for strategic decision- making (e.g., yearly flight performance trends)
02	Business Analysts	Data exploration, trend analysis, and predictive modeling
03	Operations Team	Monitoring flight delays, cancellations, and efficiency metrics
04	Marketing Team	Understanding passenger demand and customer preferences

OLAP QUERIES

1. Roll-Up : Aggregating Flight Delays by Year & Airline

- The results will show which airlines experience the highest total departure and arrival delays over different years.
- Helps airlines implement strategies to reduce delays and improve scheduling efficiency.
- Help stakeholders in the airline industry make data-driven decisions on scheduling, fleet management, and resource allocation.

Row /	Year 🏅	Airline ▼	Total_Departure_Delay	Total_Arrival_Delay
1	2019	Southwest Airline	15692786	13517583
2	2019	American Airlines	13814816	14096412
3	2019	SkyWest Airlines	13463873	13684154
4	2019	Delta Air Lines Inc.	10750245	10657128
5	2019	United Air Lines I	10222473	10581697
6	2019	JetBlue Airways	6420069	6268679
7	2019	Envoy Air	4149527	4633389
8	2019	Republic Airlines	4136433	4599890
9	2019	Comair Inc.	4081732	4106304
10	2019	Mesa Airlines Inc.	3863308	3997880

2. Drill-Down: Taxi-In and Taxi-Out Times by Airport

- Taxi-in and taxi-out times at different airports, which helps in understanding airport congestion, efficiency, and operational delays.
- Helps in deciding which airports need better infrastructure investment, Where airlines should plan buffer times for scheduling.

```
SELECT

a.Airport_Name,

ROUND(AVG(f.TaxiIn), 2) AS Avg_TaxiIn,

ROUND(AVG(f.TaxiOut), 2) AS Avg_TaxiOut

FROM _bamboo-medium-450316-m8.flight_data.fact_flight_data_f

JOIN _bamboo-medium-450316-m8.flight_data.dim_airport_a

ON f.Origin_Airport_ID = CAST(a.Airport_ID AS STRING)

WHERE a.Airport_Name IS NOT NULL

GROUP BY a.Airport_Name

ORDER BY Avg_TaxiOut DESC;
```

Row /	Airport_Name ▼	Avg_TaxiIn ▼	Avg_TaxiOut ▼
1	Williston, ND, North Dakota	8.53	23.39
2	New York, NY, New York	7.94	23.07
3	Newark, NJ, New Jersey	7.55	23.01
4	Presque Isle/Houlton, ME, Maine	12.85	22.76
5	Dickinson, ND, North Dakota	10.67	21.52
6	Charlotte, NC, North Carolina	6.21	21.31
7	Hayden, CO, Colorado	9.36	21.18
8	Aspen, CO, Colorado	9.78	21.12
9	Philadelphia, PA, Pennsylvania	7.48	21.11
10	Mammoth Lakes, CA, California	10.94	20.3

3. Dice: On-Time Performance for Flights Over a Certain Distance

- Airlines can use this data to optimize scheduling & reduce delays.
- Travelers can use it to choose airlines with better long-distance punctuality.
- Airports can use this to identify carriers causing congestion & improve operations.

```
a.Airline,
f.Distance,
COUNT(f.Flight_ID) AS Total_Flights,
SUM(CASE WHEN f.DepDel15 = 1 THEN 1 ELSE 0 END) AS Delayed_Flights
FROM 'bamboo-medium-450316-m8.flight_data.fact_flight_data' f

JOIN 'bamboo-medium-450316-m8.flight_data.dim_airline' a

ON CAST(f.Airline_ID AS INT64) = a.Airline_ID

WHERE f.Distance > 1000
GROUP BY a.Airline, f.Distance
ORDER BY f.Distance DESC;
```

Row /	Airline ▼	Distance	Total_Flights	Delayed_Flights
1	United Air Lines Inc.	5812.0	20	0
2	Hawaiian Airlines Inc.	5095.0	935	155
3	Hawaiian Airlines Inc.	4983.0	1493	263
4	Delta Air Lines Inc.	4983.0	28	10
5	United Air Lines Inc.	4962.0	1444	245
6	United Air Lines Inc.	4904.0	200	61
7	United Air Lines Inc.	4817.0	692	104
8	Hawaiian Airlines Inc.	4757.0	201	25
9	American Airlines Inc.	4678.0	476	76
10	Delta Air Lines Inc.	4502.0	1577	248

4. Pivot: Average Arrival Delay by Airline

- Airlines can use this to benchmark their performance against competitors and develop strategies to improve operational efficiency.
- Travelers can make informed choices by selecting airlines with a strong on-time arrival record.
- Airports can manage their ground operations more effectively by understanding which airlines contribute to congestion.

```
SELECT * FROM (
 SELECT
    a.Airline.
    d.Year.
    AVG(f.ArrDelayMinutes) AS Avg_Arrival_Delay
 FROM `bamboo-medium-450316-m8.flight_data.fact_flight_data` f
 JOIN `bamboo-medium-450316-m8.flight_data.dim_airline` a
   ON CAST(f.Airline_ID AS INT64) = a.Airline_ID
 JOIN `bamboo-medium-450316-m8.flight_data.dim_date` d
    ON f.Date_ID = d.Date_ID
 GROUP BY a.Airline, d.Year
PIVOT (
 AVG(Avg_Arrival_Delay)
 FOR Year IN (2019, 2020, 2021)
```

Row /	Airline ▼	_2019 ▼	_2020 ▼	_2021 ▼
1	Allegiant Air	15.55652365405	13.33111095180	21.27442264002
2	Delta Air Lines Inc.	10.78629386908	6.209070238867	8.509148803307
3	Mesa Airlines Inc.	18.11938850893	10.34442677778	18.24994985603
4	Endeavor Air Inc.	14.63693001112	5.877866220211	6.729974272142
5	Horizon Air	8.499155000630	5.351231500191	7.465947329919

5. Cube: Total Flights by Airline, SELECT a.Air d.Mort

- Airports with high total flights may serve as key hubs, influencing airline scheduling, resource allocation.
- This helps to optimize flight schedules, increase capacity during peak seasons, and reduce costs in off-peak months.

```
a.Airline,
d.Month,
ap.Airport_Name,
COUNT(*) AS total_flights

FROM <u>bamboo-medium-450316-m8.flight_data.fact_flight_data</u> f

JOIN <u>bamboo-medium-450316-m8.flight_data.dim_airline</u> a

ON CAST(f.Airline_ID AS INT64) = a.Airline_ID

JOIN <u>bamboo-medium-450316-m8.flight_data.dim_date</u> d

ON f.Date_ID = d.Date_ID

JOIN <u>bamboo-medium-450316-m8.flight_data.dim_airport</u> ap

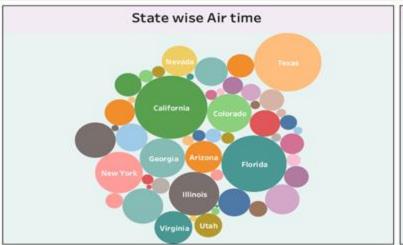
ON CAST(f.Origin_Airport_ID AS INT64) = CAST(ap.Airport_ID AS INT64)

GROUP BY a.Airline, d.Month, ap.Airport_Name

ORDER BY total_flights DESC;
```

Row /	Airline ▼	Month	Airport_Name ▼	total_flights
1	Delta Air Lines Inc.	3	Atlanta, GA, Georgia	55518
2	Delta Air Lines Inc.	8	Atlanta, GA, Georgia	52172
3	Delta Air Lines Inc.	1	Atlanta, GA, Georgia	50391
4	Delta Air Lines Inc.	10	Atlanta, GA, Georgia	50238
5	Delta Air Lines Inc.	7	Atlanta, GA, Georgia	49401

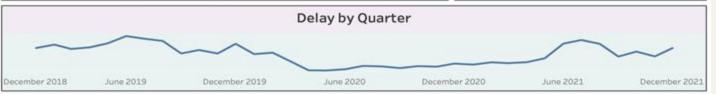
Visualization





			Taxi Time in City					
Dallas/Fort Worth, TX	Denver, CO	Los Angeles, CA	Washington, DC					
New York, NY	Charlotte, NC	Houston, TX	Detroit, MI					
	TX	TX	TX					





Summary







Challenges

- Handling missing & duplicate data
- Integrating with Google cloud platform
- Optimizing schema design

Learnings

- Google BigQuery Performance
- Understanding OLAP Operations
- Visualization & Reporting in Tableau

Future Scope

- Real-Time Flight Delay Prediction
- Automating ETL Workflows
- Flight Optimization System

Thank You

