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Moritz Baur
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2025-03-17

Problem and Motivation

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- Flight delays are disruptive and costly.
- Passengers lose time ⏱ and confidence.
- Airlines and airports face financial losses 💼 and reduced operational efficiency.

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📈 Motivation

- Tunisair aims to implement a predictive solution to anticipate delays and mitigate their impact.

🎯 Project Objective

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🥅 Goal

Use machine learning to predict the length of flight delays (in minutes).

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💥 Impact

- ✔ Better scheduling
- ✔ Reduced operational inefficiencies
- ✔ Improved passenger satisfaction

Dataset and Evaluation

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Data Source

📁 Flight data provided by Zindi, consisting of a train/test format for model development

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Prediction Target:

🕒 Delay duration in minutes

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Performance Metric:

📉 Root Mean Square Error (RMSE)

Exploratory Data Analysis (EDA)

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🔍 Initial Insights from EDA

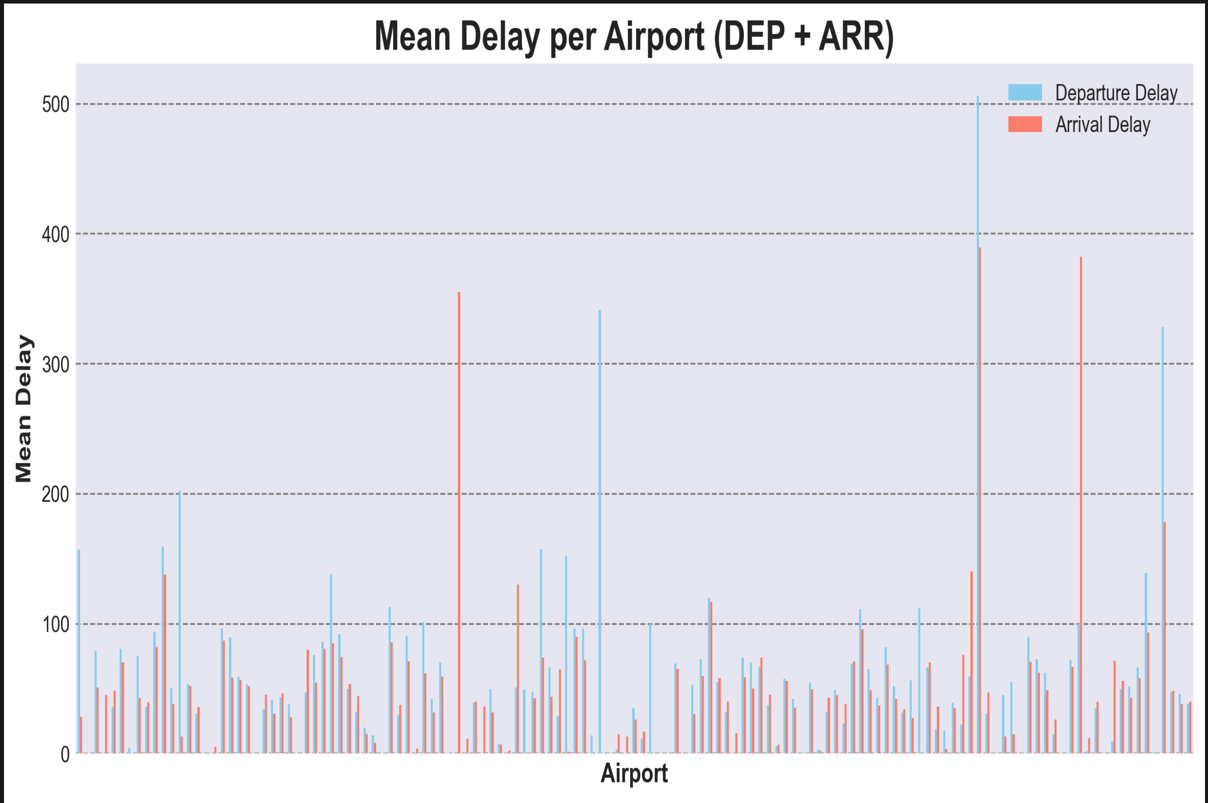
We analysed how delays are distributed based on:

- Departure airports
- Arrival airports
- Temporal trends across the years 2016–2018

Column Description

Column	Description
ID	Unique flight identifier
DATOP	Date of flight
FLTID	Flight number
DEPSTN	Departure point
ARRSTN	Arrival point
STD	Scheduled time of departure
STA	Scheduled time of arrival
STATUS	Flight status
AC	Aircraft code
target	Flight delay (min)

Mean Delay per Airport by Departure and Arrival



Deriving flight time from STD and STA

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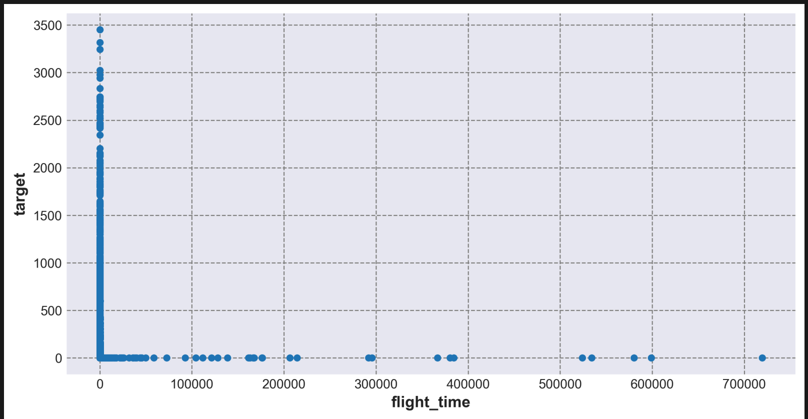

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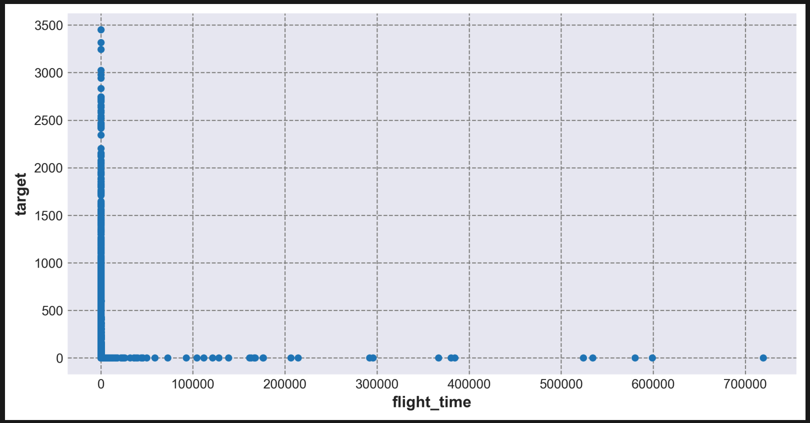

$\Rightarrow$

DERIVING FLIGHT TIME FROM STD AND STA

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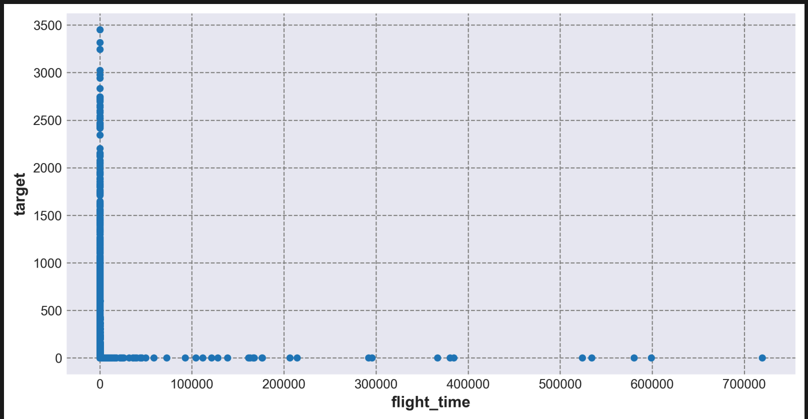
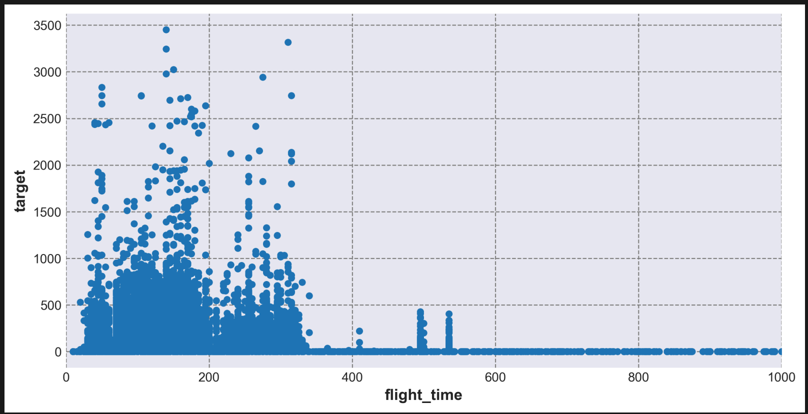
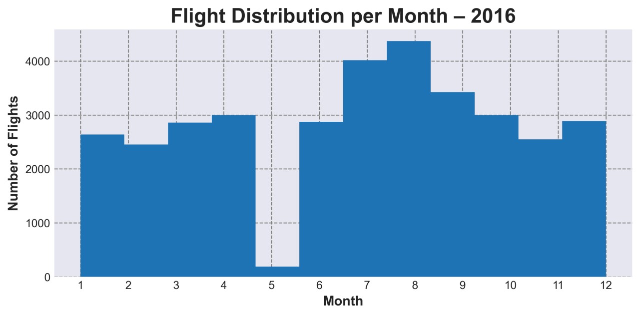
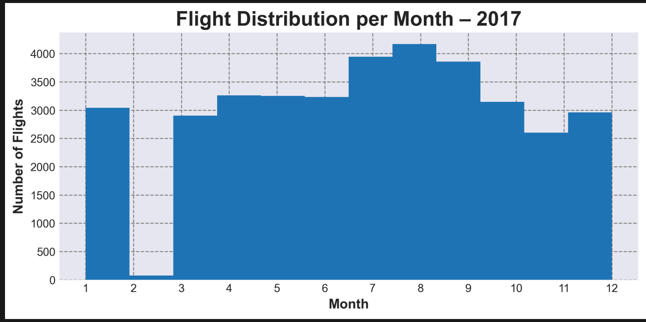


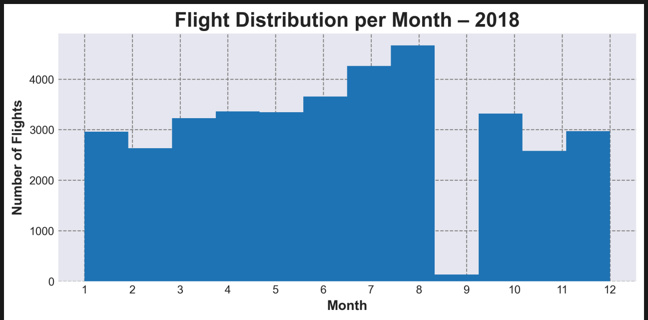
⇒

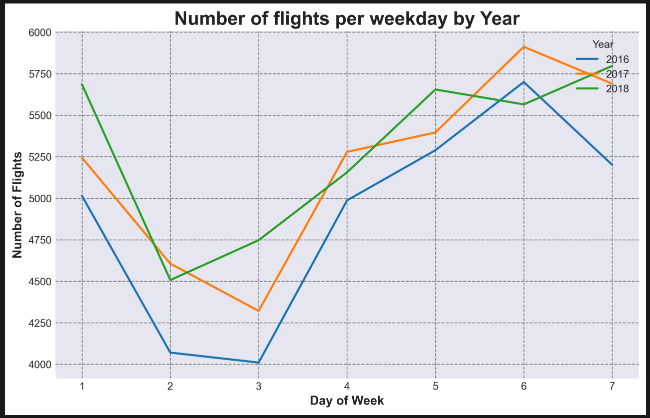


DISSECTING DATOP INTO YEAR, MONTH AND DAY OF THE WEEK









Baseline Model

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Approach

A simple linear regression model using only the day of the week (or aircraft code) as the predictor.

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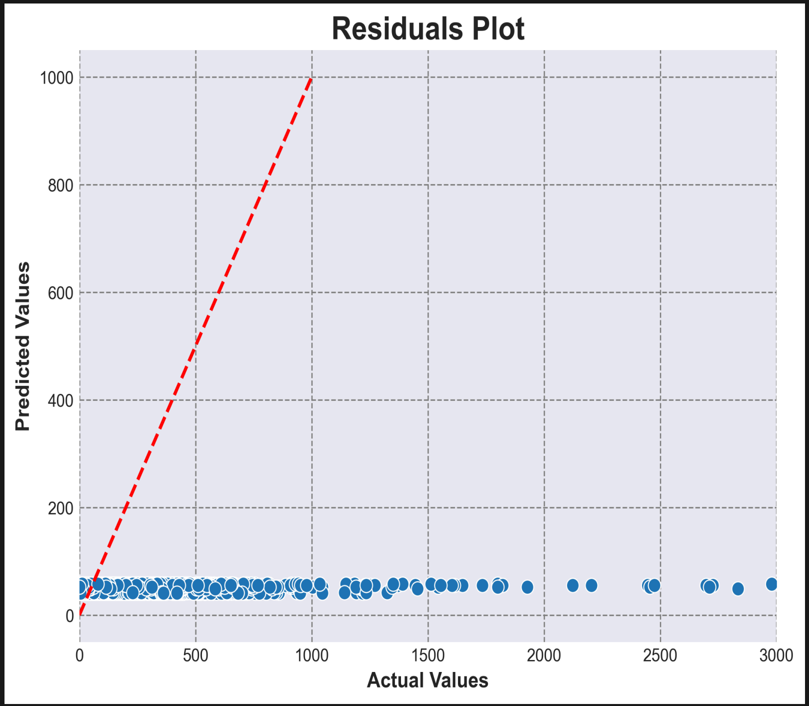
Performance

📊 RMSE ≈ 114.69

🤖 R_2 ≈ 3.01 %



ML Model

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Many categorical variables …

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Many categorical variables …

… but there is:

ML Model

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CatBoost

Machine-generated image—no animals were harmed

ML Model

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Approach

A regression model using CatBoost with the following predictors: *Flight Status; Aircraft Code; Departure and Arrival Point; Year, Month and Weekday of Departure Time*

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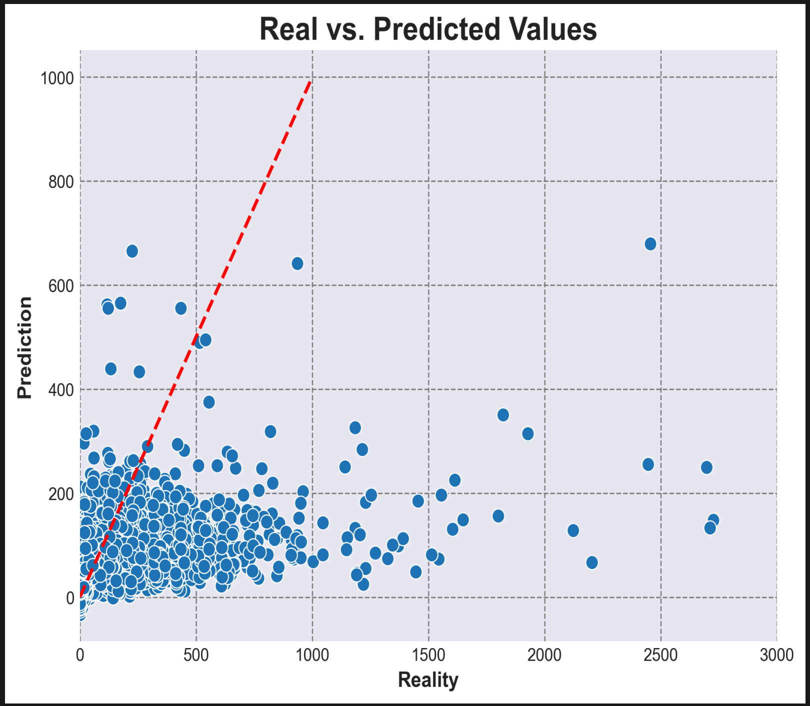
A regression model using CatBoost with the following predictors: *Flight Status; Aircraft Code; Departure and Arrival Point; Year, Month and Weekday of Departure Time*

Performance

📊 RMSE ≈ 96.14 (< 100)

🤖 R_2 ≈ 30.48 %



💬 Questions and Feedback

We're happy to answer your questions and look forward to your feedback.