

**What is the best predictor for  
taxi out time?**

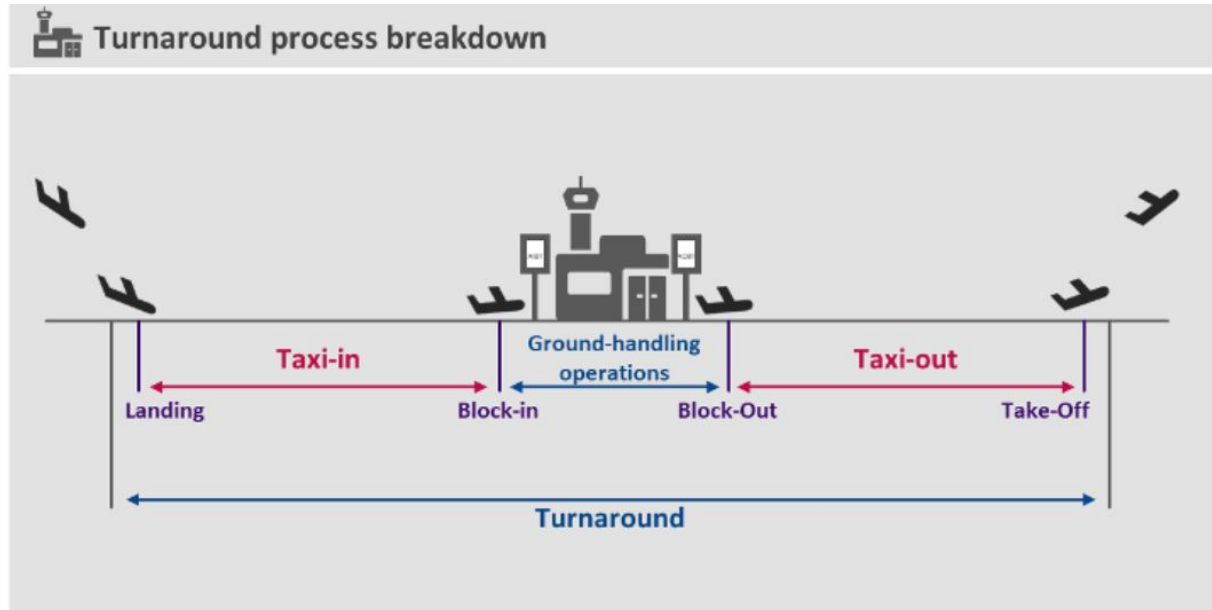
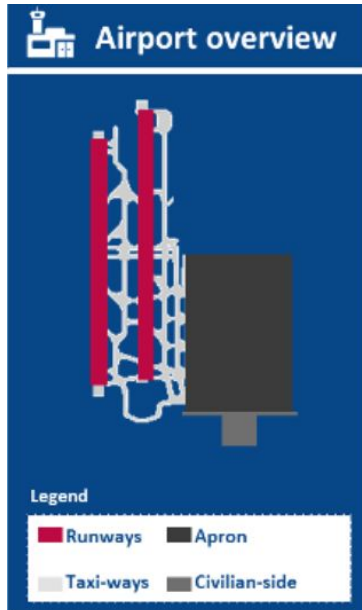




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# How does an airport work?



# Reducing the taxi-out time

**Taxi-out:** timespan between block-out and take-off

It affects:

- Airline companies
- Airports
- Environment



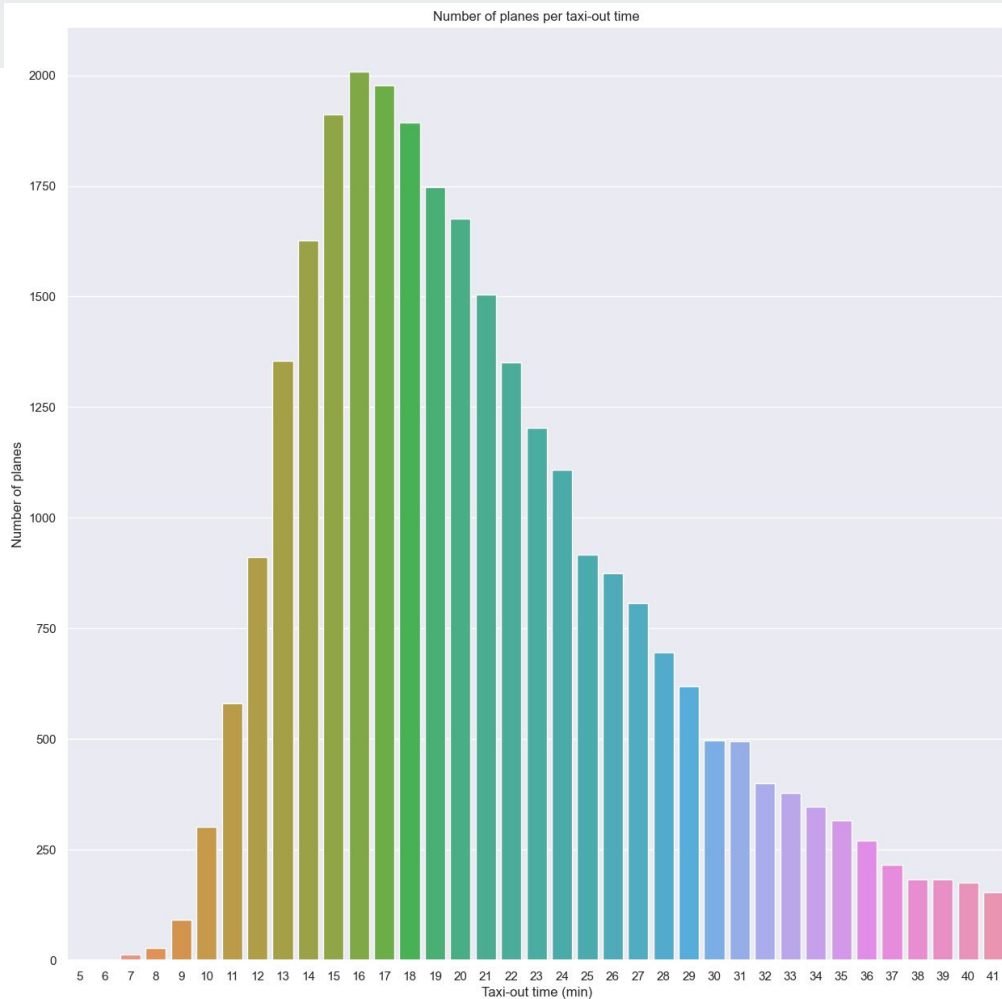
**Solution:** Using linear regression to find the best predictor

# The dataset

Data about flights leaving JFK Airport (Nov 2019 - Dec 2020)

- 28818 entries after removing 2
- 23 variables
- Target variable: taxi\_out

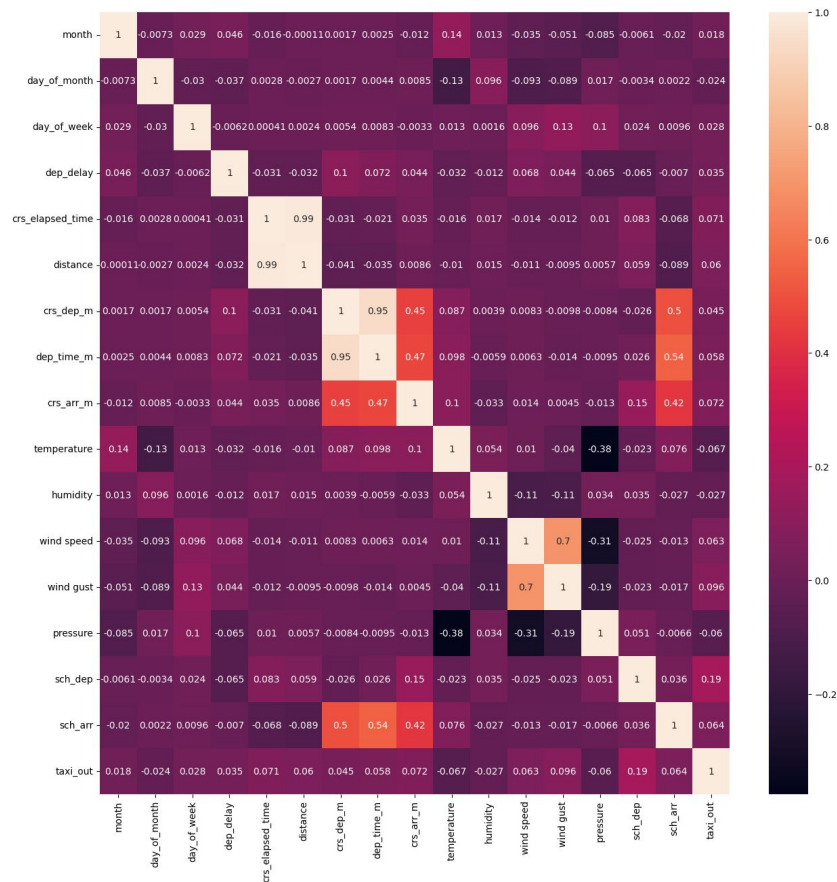
```
Index: 28818 entries, 0 to 28819
Data columns (total 23 columns):
 #   Column              Non-Null Count  Dtype
---  -
 0   month               28818 non-null  int64
 1   day_of_month        28818 non-null  int64
 2   day_of_week         28818 non-null  int64
 3   op_unique_carrier   28818 non-null  object
 4   tail_num            28818 non-null  object
 5   dest                28818 non-null  object
 6   dep_delay           28818 non-null  int64
 7   crs_elapsed_time    28818 non-null  int64
 8   distance            28818 non-null  int64
 9   crs_dep_m           28818 non-null  int64
10   dep_time_m          28818 non-null  int64
11   crs_arr_m           28818 non-null  int64
12   temperature         28818 non-null  int64
13   dew_point           28818 non-null  object
14   humidity            28818 non-null  int64
15   wind                28818 non-null  object
16   wind_speed          28818 non-null  int64
17   wind_gust           28818 non-null  int64
18   pressure            28818 non-null  float64
19   condition           28818 non-null  object
...
21   sch_arr             28818 non-null  int64
22   taxi_out            28818 non-null  int64
dtypes: float64(1), int64(16), object(6)
memory usage: 5.3+ MB
```



## Frequency bar plot

- Most frequent : 16min
- Mean: 20.85 min
- Min: 5
- Max: 41

Considered delayed if over  
15 min



## Correlation Matrix

- All below 0.1
- Except for sch\_dep (number of flights scheduled for departure) at 0.19

Next top variables:

- Wind gust: 0.096
- Crs\_elapsed\_time (schedule journey time of the flight): 0.071

# Evaluation of the model

**Linear Regression** with number of flights scheduled on for departure

```
R squared: 0.04  
Mean Absolute Error: 5.353282616449877  
Mean Square Error: 45.10840350858983  
Root Mean Square Error: 6.716278992760041
```

**Multiple Regression** with the 3 highest correlated variables

```
R squared: 0.05  
Mean Absolute Error: 5.318760437051704  
Mean Square Error: 44.56825084333637  
Root Mean Square Error: 6.675945689064312
```



# Best model



Multiple Regression with the all  
numerical variables

```
R squared: 0.07  
Mean Absolute Error: 5.260479190557299  
Mean Square Error: 43.62204291226953  
Root Mean Square Error: 6.604698548175346
```

# Conclusion



Number of flights scheduled for departure is the best predictor here.  
But not the only one.

## Further investigation:

- Clean more data
- More exploration: time series
- Feature engineer : encoding, etc
- Explore categorical data
- Use other models

—> Optimise time-out prediction —> £££



***THANK YOU!***

# Appendix



How does an airport work?

1. **ALDT** : Actual Landing Time - wheels on the ground
2. **AIBT** : Actual In-Block Time - reach dock at registered timestamp
3. Ground-handling teams (catering, cleaning, fueling, boarding...)
4. **AOBT** : Actual Off-Block Time - left dock
5. **ATOT** : Actual Take-Off Time - wheels off the ground



## The issues with taxi-out

**For airline companies:** the basics of airline companies' finances in airports is that an aircraft that is not airborne is an aircraft losing money. So, by providing a better taxi-out time prediction and reducing queues at the runway's entry point, the solution ensures less time spent on the ground for A/Cs, and thus less money lost for airline companies

**For airports:** for an airport, the most A/Cs are operated per day, the more money it makes. So by providing a forecast that smoothens the A/C flow, the taxi-out time prediction solution potentially increases the amount of aircrafts that can be operated per day at the airport and thus the money generated by the airport

**For the environment:** when an aircraft is queuing at the runway's entry point, one should know that its engines are still running, so that's kerosene that is used and GHG emissions generated for virtually nothing. By reducing the queuing time, the solution also reduces the GHG emission levels at airports.

<https://leonard.vinci.com/en/taxi-out-time-prediction/>



# Dataset

- **Table 1.** Attribute description for the data set. :

<https://dl.acm.org/doi/fullHtml/10.1145/3497701.3497725>

- From **Kaggle**:

<https://www.kaggle.com/deepankurk/flight-take-off-data-jfk-airport/tasks?taskId=4868>



## **Github link to code of models**

Made & presented on : 02/06/2023