

Prediction of Flight Departure and Arrival Routes with Gradient Boosted Decision Trees

EUROCONTROL Innovation Hub
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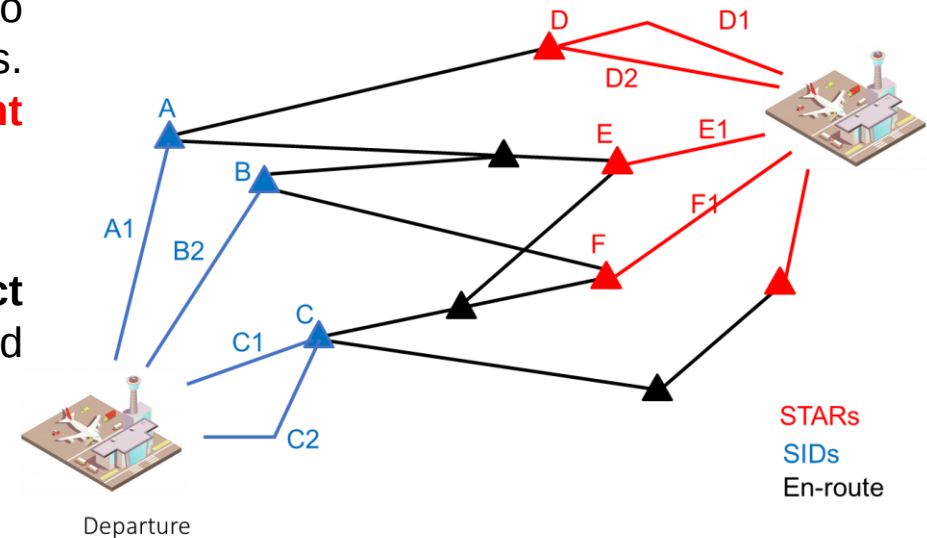


11th SESAR Innovation Days



Introduction

- Motivation:** **Improving traffic demand prediction** is key for an efficient Network and Artificial Intelligence is a key enabler to achieve this goal. The Network Research Unit (NET) is currently developing an AI algorithm to predict flight plans between city pairs. And **having a better prediction of SID and STAR should improve flight plans prediction.**
- Objective:** Design and train a **Machine Learning model able to predict which SID/STAR** each departing/arriving flight is going to use with a lead time.
- Impact:**
 - Network:** Reduce air traffic demand uncertainty with more accurate demand and capacity balance measures.
 - Airport:** Improve the departure sequencing tools throughput.
 - Environment:** Inform the local communities about the expected noise levels in the next hours.



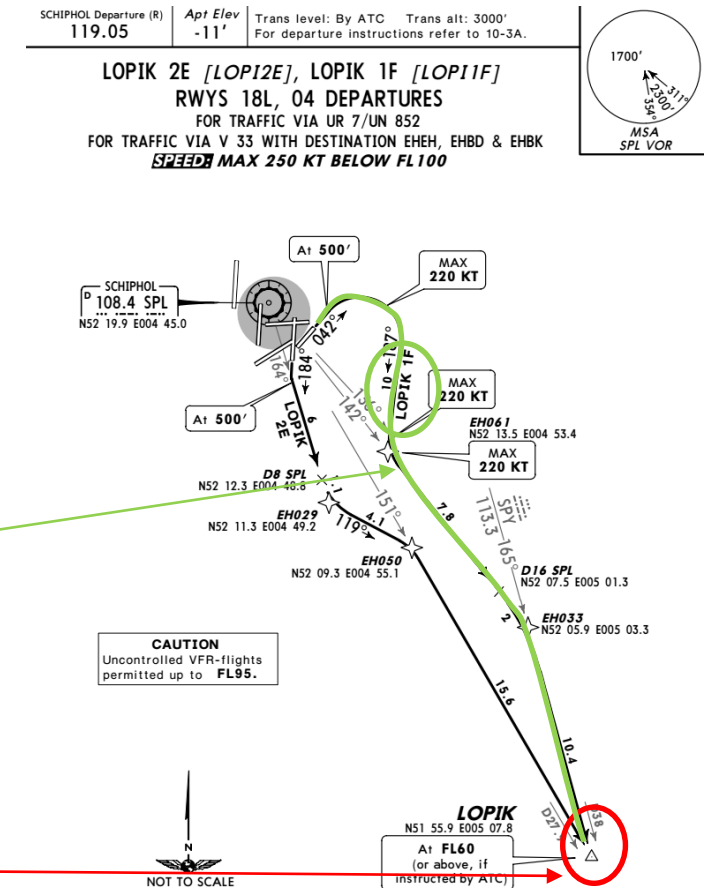
Prediction target

- SIDs are named after the final waypoint of the procedure
 - Followed by a version number that is incremented by one each time the procedure is modified
 - And a single letter that designates the associated runway
- For STARs, the equivalent nomenclature is used, but the initial waypoint of the procedure is used instead.

=> Predict this initial/final waypoint !

- Example:
 - “**LOPIK1F**” refers to a SID of Amsterdam-Schipol airport (EHAM) that connects RWY04 with the LOPIK waypoint.
 - **Prediction target: LOPIK.**

- Why not keep the character coding the runway as well ?



1. EFDs (all 2019 flights from/to EHAM)

	iflpid	fltstate	event	tstamp	adep	ades	ptrte_sid	ptrte_star	taxitime	arctyp	aoopr
0	AA09360977	FI	IFP	2019-01-01 05:55:47	EHAM	LFPO	LARAS1X	MOPI7W	14	B737	TRA
1	AA09360977	FI	PTX	2019-01-01 09:58:17	EHAM	LFPO	LARAS1X	MOPI7W	14	B737	TRA
2	AA09360977	FI	EDI	2019-01-01 14:50:05	EHAM	LFPO	WOODY1W	MOPI7W	14	B737	TRA
3	AA09360977	FI	EDI	2019-01-01 15:41:50	EHAM	LFPO	KUDAD1V	MOPI7W	17	B737	TRA
4	AA09360977	FI	TDI	2019-01-01 15:50:04	EHAM	LFPO	KUDAD1V	MOPI7W	17	B737	TRA
5	AA09360977	FI	ICH	2019-01-01 16:57:53	EHAM	LFPO	KUDAD1V	MOPI7W	17	B737	TRA
6	AA09360977	TA	TSA	2019-01-01 17:10:04	EHAM	LFPO	KUDAD1V	MOPI7W	17	B737	TRA

...

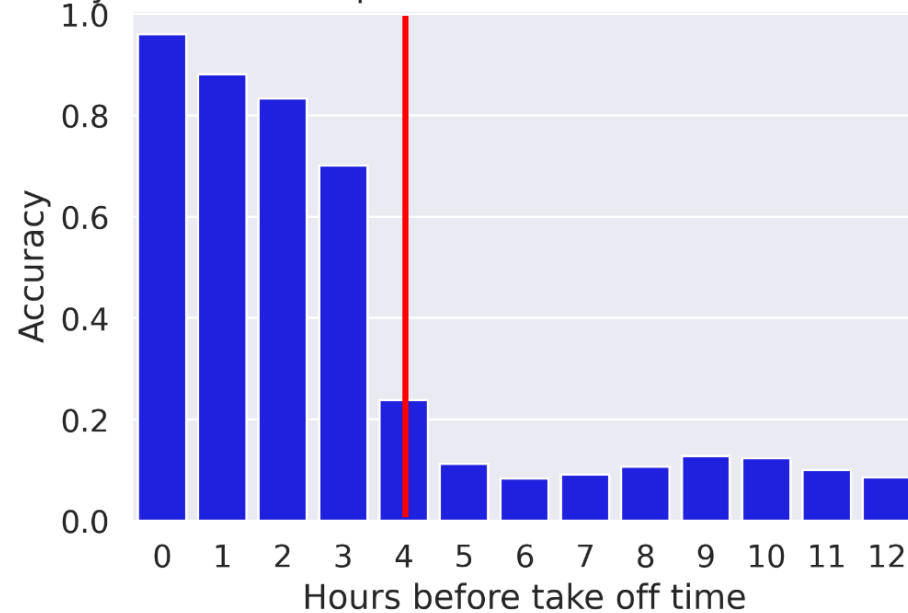
19	AA09360977	AA	CPR	2019-01-01 18:33:01	EHAM	LFPO	KUDAD1V	MOPI7W	20	B737	TRA
20	AA09360977	AA	CPR	2019-01-01 18:36:46	EHAM	LFPO	KUDAD1V	MOPI7W	20	B737	TRA
21	AA09360977	AA	CPR	2019-01-01 18:46:35	EHAM	LFPO	KUDAD1V	MOPI7W	20	B737	TRA
22	AA09360977	AA	CPR	2019-01-01 18:52:42	EHAM	LFPO	KUDAD1V	DCT	20	B737	TRA
23	AA09360977	TE	TTE	2019-01-01 19:17:10	EHAM	LFPO	KUDAD1V	DCT	20	B737	TRA

2. Weather data – METARs

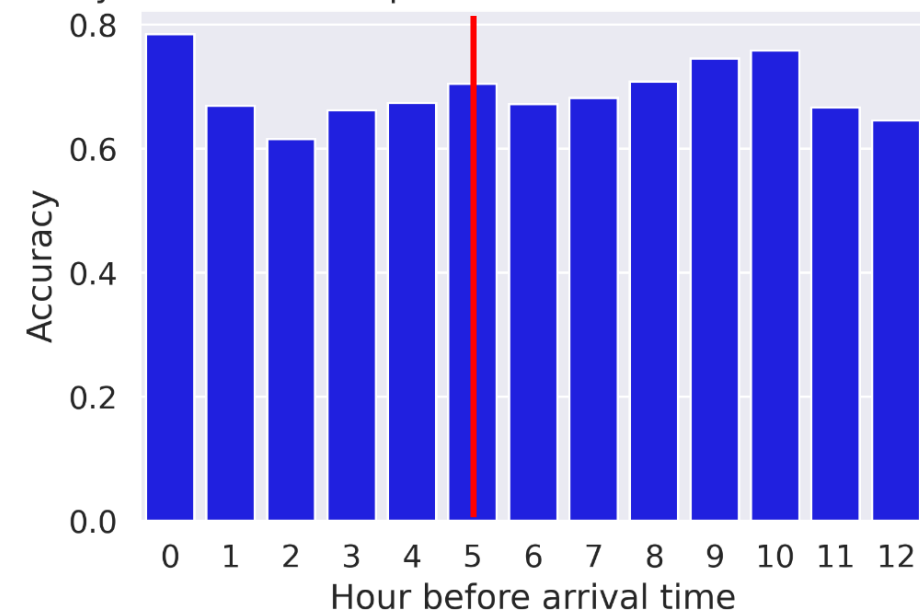
```
print(Metar('EHAM 010025Z 27013KT 9999 OVC025 09/05 Q1030 NOSIG').string())
station: EHAM
type: routine report (automatic report)
time: Tue Jun 1 00:25:00 2021
temperature: 9.0 C
dew point: 5.0 C
wind: W at 13 knots
visibility: greater than 10000 meters
pressure: 1030.0 mb
sky: overcast at 2500 feet
METAR: EHAM 010025Z 27013KT 9999 OVC025 09/05 Q1030 NOSIG
```

Look ahead time selection

Volatility of ETFMS SID predictions as a function of time of take off



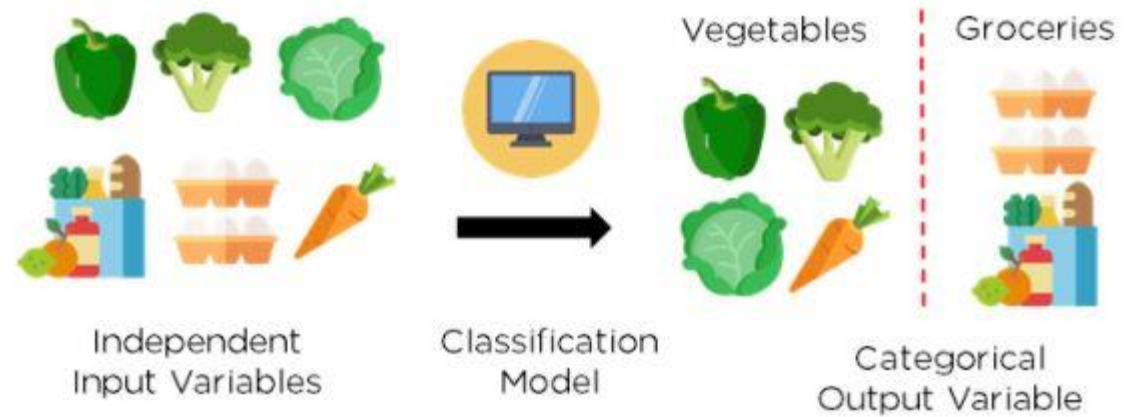
Volatility of ETFMS STAR predictions as a function of time of arrival



Target collected from last message that has been sent. (TEE event)

Supervised learning

- Classification task!
- Input data:
 - 536 130 flights data
 - + 20M ETFMS messages
- Target:
 - 23 different SID routes
 - 11 different STAR routes



Supervised learning – Input Features

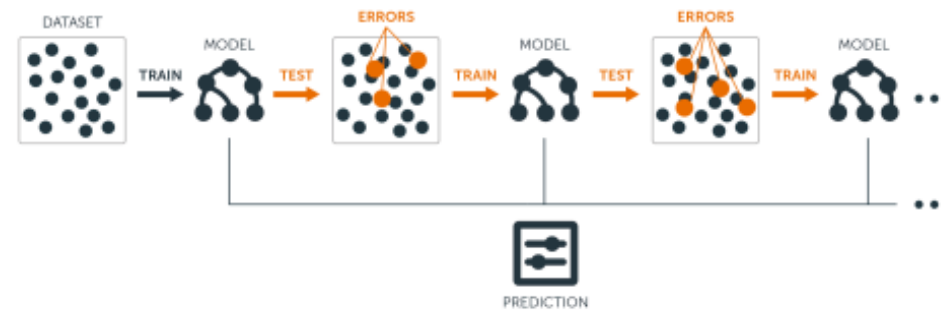
Category	Feature	Type
Flight	Destination (resp. departure) airport Expected SID (resp. STAR) Aircraft type Aircraft operator	Categorical
	Expected taxi time	Numerical
Weather	Sky condition (OVC, SCT, FEW, BKN, ...) Wind direction (N, NNE, NE, ENE, E, ...)	Categorical
	Visibility Temperature Dew point Pressure Wind speed	Numerical
Calendar	Month Day of the week Hour of the day	Categorical
Traffic	Departure traffic demand Arrival traffic demand Traffic demand for each SID (resp. STAR)	Numerical

Supervised learning – Data Issues

- Problems:
 - Duplicate (EFD messages might be very similar)
 - Imbalance
- Solutions:
 - At the selected look-ahead time (ex: 4h ahead for SID), keep only the last message sent by each flight.
 - Use class weights (give more importance to classes with fewer samples)
 - Stratified data split :
 - 80% training
 - 20% testing

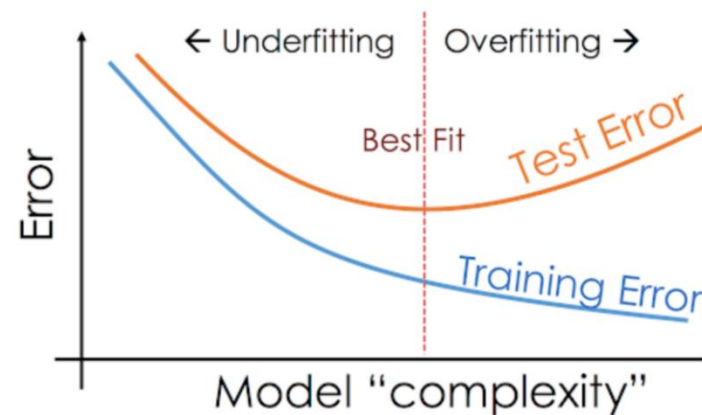
Model

- **LightGBM** is a gradient boosting framework that uses tree-based learning algorithms.
 - State of the art performance
 - Airport scale
 - May work with simple common inputs



LightGBM – Parameters Tuning

- Main problem faced was the overfitting!



- Parameters tuning to control overfitting!
- Cross Validation with 5 folds & Stepwise optimization with TPE (Tree-structured Parzen Estimator)

- Optimized parameters:

Hyper-parameter	Procedure	
	SID	STAR
lambda_l1	6.7e-6	0.
lambda_l2	1.68	0.
num_leaves	304	56
feature_fraction	0.52	0.68
bagging_fraction	0.47	1.
min_child_samples	44	20

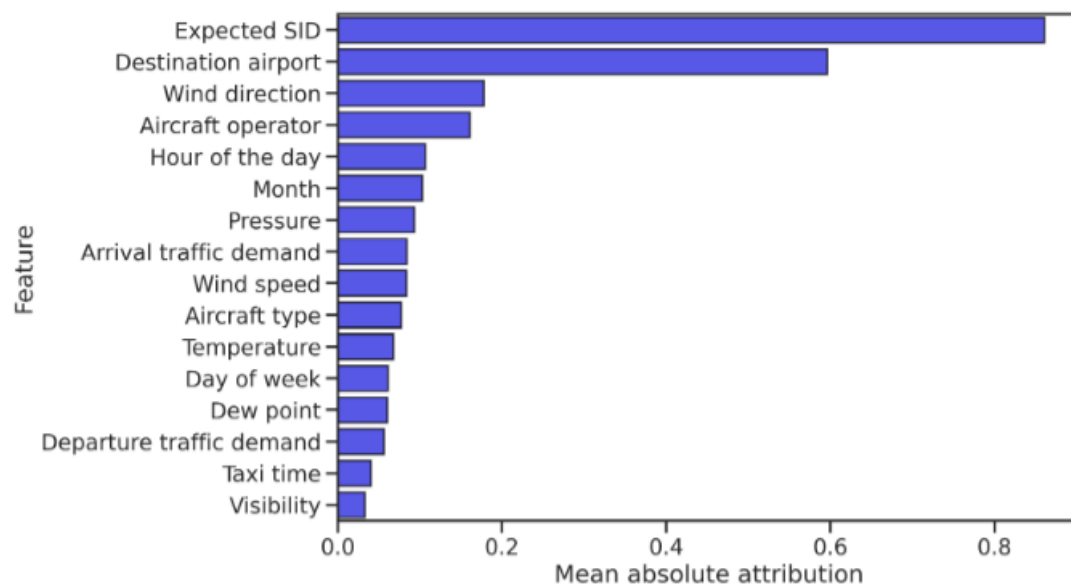
Results

- Metrics: [sklearn.metrics.classification_report](#)
 - Accuracy
 - Weighted & Macro *:
 - Precision
 - Recall
 - F1-score

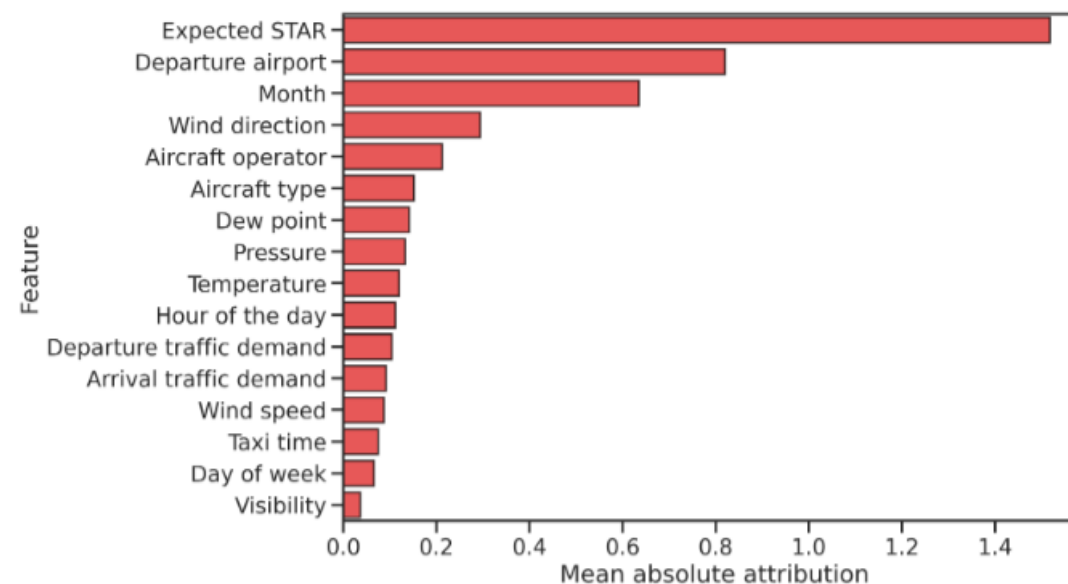
Procedure	Model	Macro average (weighted average)			
		Precision	Recall	F1-score	Accuracy
SID	Baseline	0.40 (0.76)	0.31 (0.23)	0.17 (0.30)	0.23
	GBDT	0.85 (0.93)	0.73 (0.93)	0.76 (0.93)	0.93
STAR	Baseline	0.76 (0.85)	0.55 (0.72)	0.51 (0.69)	0.72
	GBDT	0.81 (0.87)	0.77 (0.87)	0.78 (0.87)	0.87

* macro average (averaging the unweighted mean per label), weighted average (averaging the support-weighted mean per label)

Feature Importance



(a) SID model

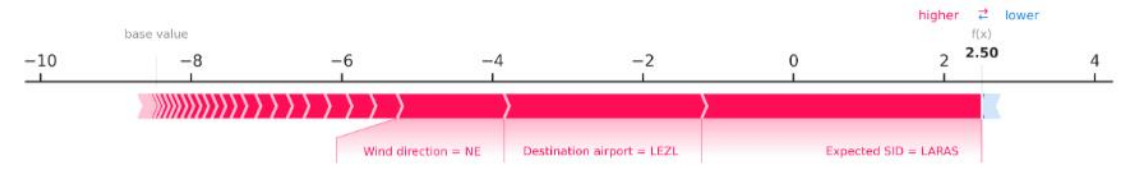


(b) STAR model

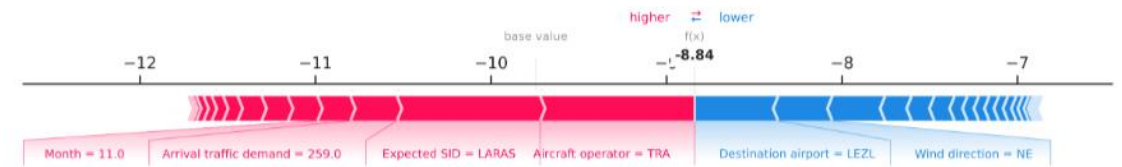
Illustrative Results



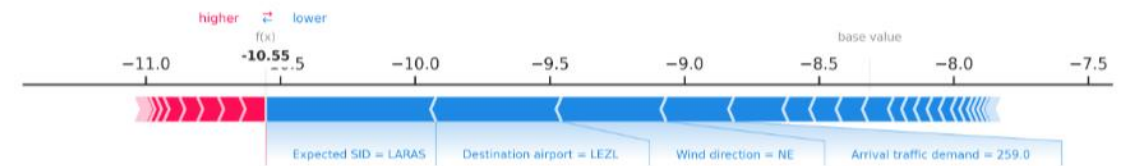
Illustrative example of SID prediction – EHAM to LEZL operated by TRA during November 2019, when the wind was blowing from NE



(a) Actual SID (WOODY)



(b) Expected SID (LARAS)



(c) SID in the opposite direction (WISPA)

Force of the features for illustrative example

Conclusion

LGBM could highly improve demand prediction for complex airports (like EHAM).

- Huge accuracy improvement (from 23% to 93%) for SID and smaller improvement (from 72% to 87%) for STAR.

Explainability of the model makes it convenient to interpret model predictions and build more trust on it.

- The comprehensive feature importance analysis reveals that predictions rely mainly on the *Expected procedure*, *Destination/Departure airport* and *Wind direction*.

Perspectives and future work

- A simplified variant model using only the most important features could be investigated.
- Train and evaluate the model in other major airports.
- Comparison with other state-of-the-art models, such as artificial neural networks.

Thank You
Any Questions ?