

Improving the Predictability of Take-off Times with Machine Learning

A case study for the Maastricht upper area control centre area of responsibility



9th SESAR Innovation Days

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2 – 6 December 2019, Athens, Greece



Outline

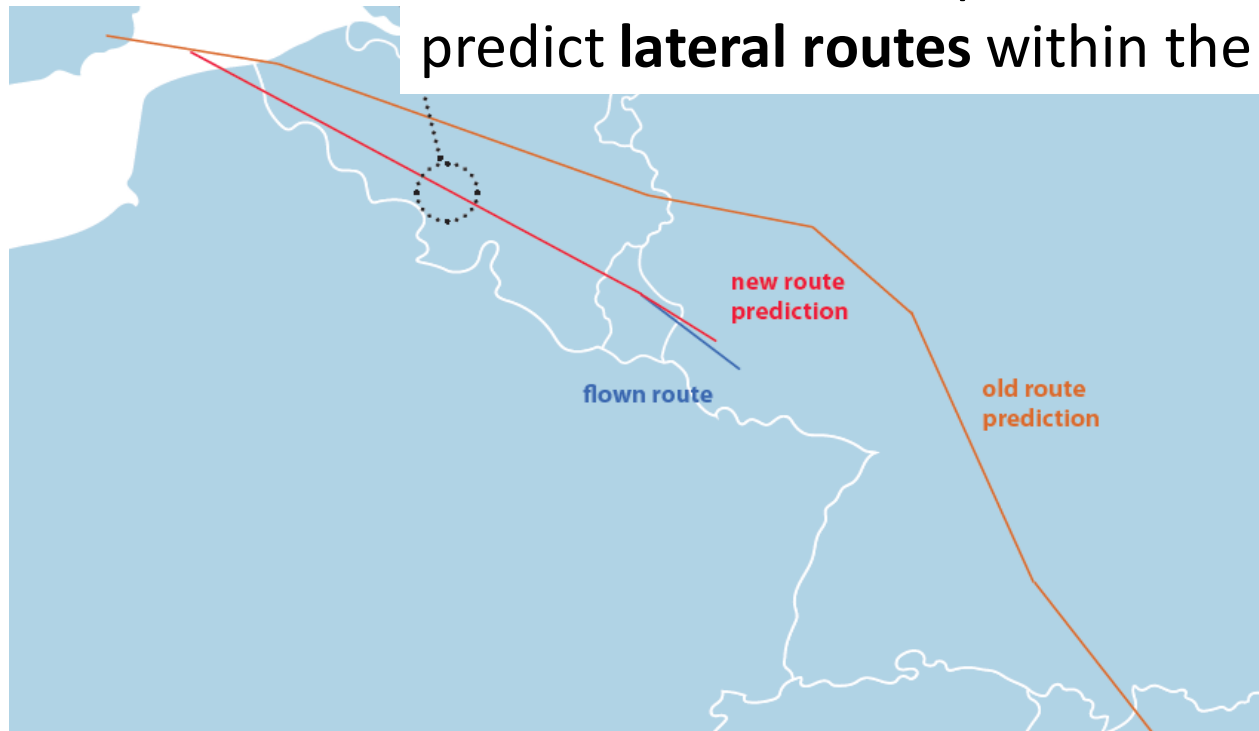
- Introduction
- Data set
- Models
- Set up of the experiment
- Results
- Conclusions

Introduction: the weakness of state-of-the-art trajectory predictors

- **16.2 M** of flights in Europe in **2040** (**57%** more traffic than in **2017**)
- **Balancing the demand** and the **capacity** has become critically important
- **Demand-capacity unbalances** are difficult to predict due to:
 - Lack of **detailed** and **up-to-date** flight information
 - Discrepancy between **scheduled** and **flown** trajectories
- The use of **historical data** by means of **Artificial Intelligence (AI)** has potential to improve the accuracy of trajectory predictions

Introduction: AI-based trajectory predictions

- **MUAC** has developed an **Artificial Neural Network (ANN)** that is able to predict **lateral routes** within the MUAC Area Of Responsibility (AoR)

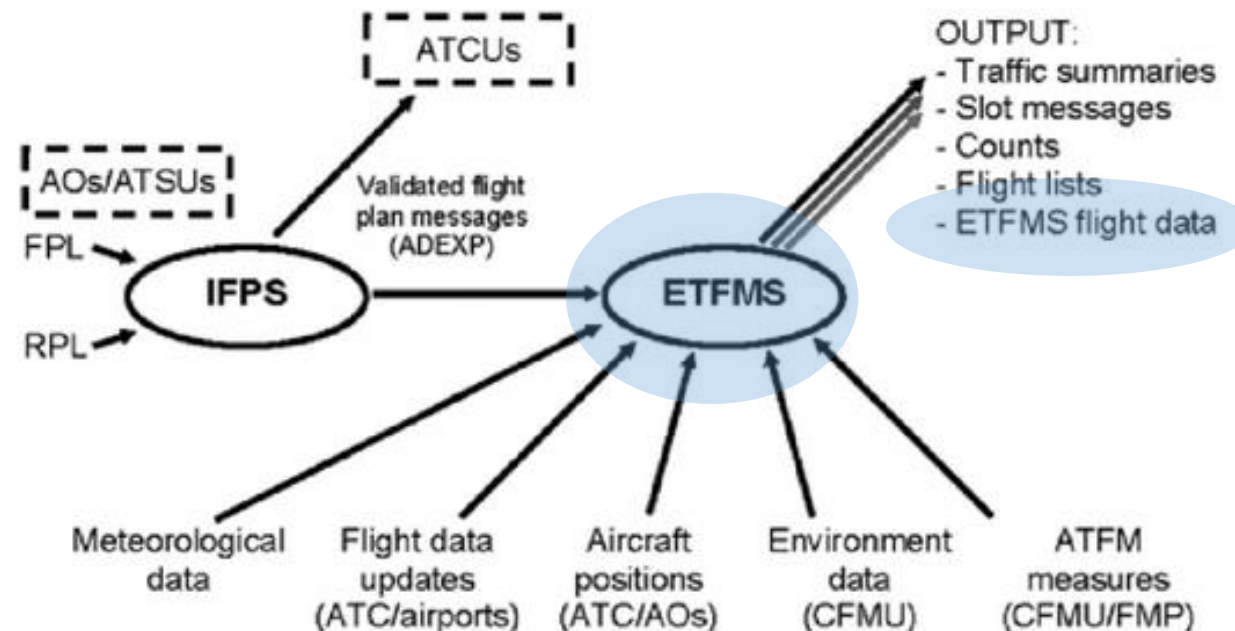


- **Operational** since **January 2018**
- **On-going** research to predict the **vertical profile (altitude and speed)**
- **Any delay** is in fact a distortion of the trajectory as much as a change of the lateral route or the vertical profile

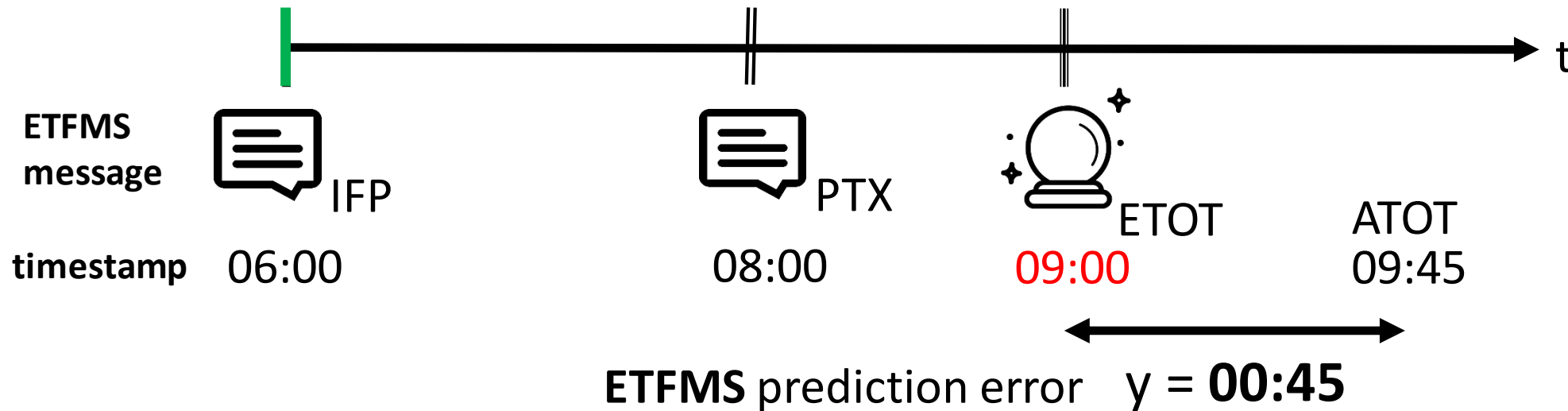
H. Naessens, T. Philip, M. Piatek, K. Schippers, and R. Parys, "Predicting flight routes with a Deep Neural Network in the operational Air Traffic Flow and Capacity Management system," EUROCONTROL Maastricht Upper Area Control Centre, Maastricht Airport, The Netherlands, 2017

Introduction: Current take-off time predictions

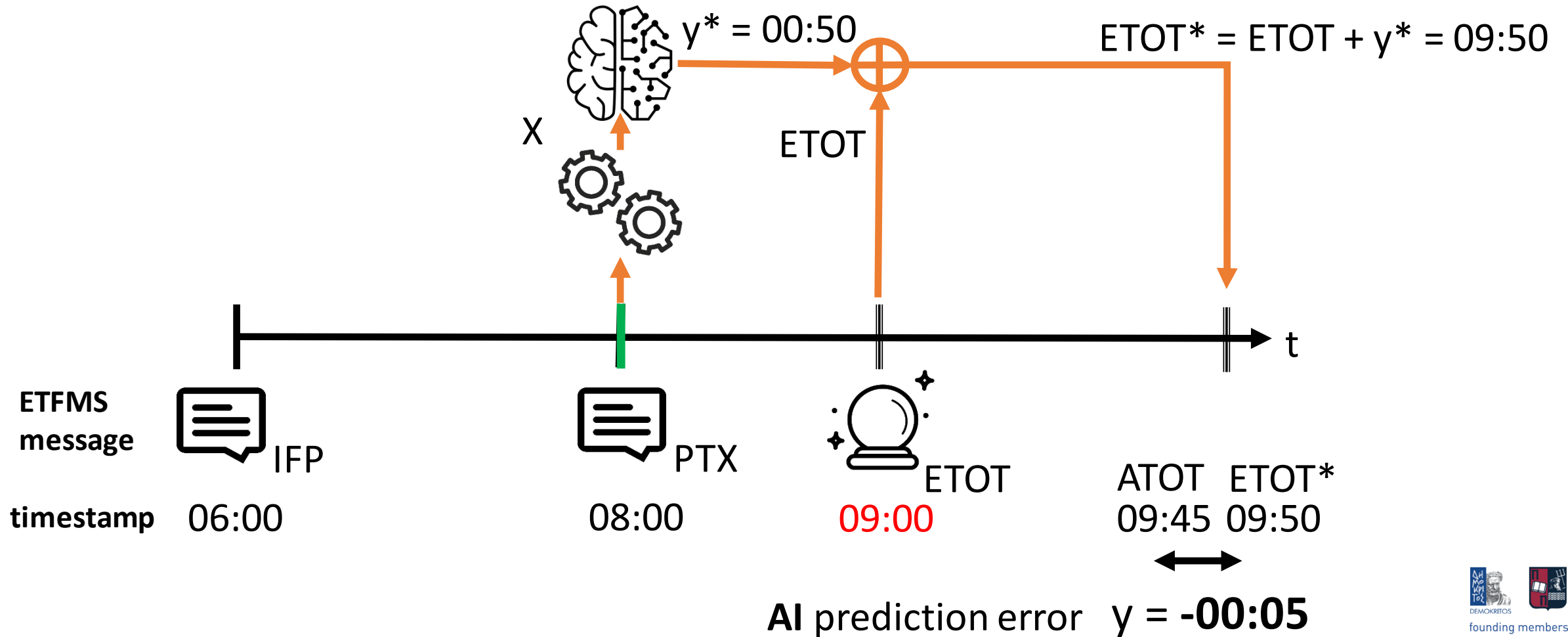
- At present, the **Estimated Take-Off Times (ETOTs)** are obtained from the **Enhanced Traffic Flow Management System (ETFMS) flight data (EFD)**
- **ETOTs reported in the EFD are not accurate enough**



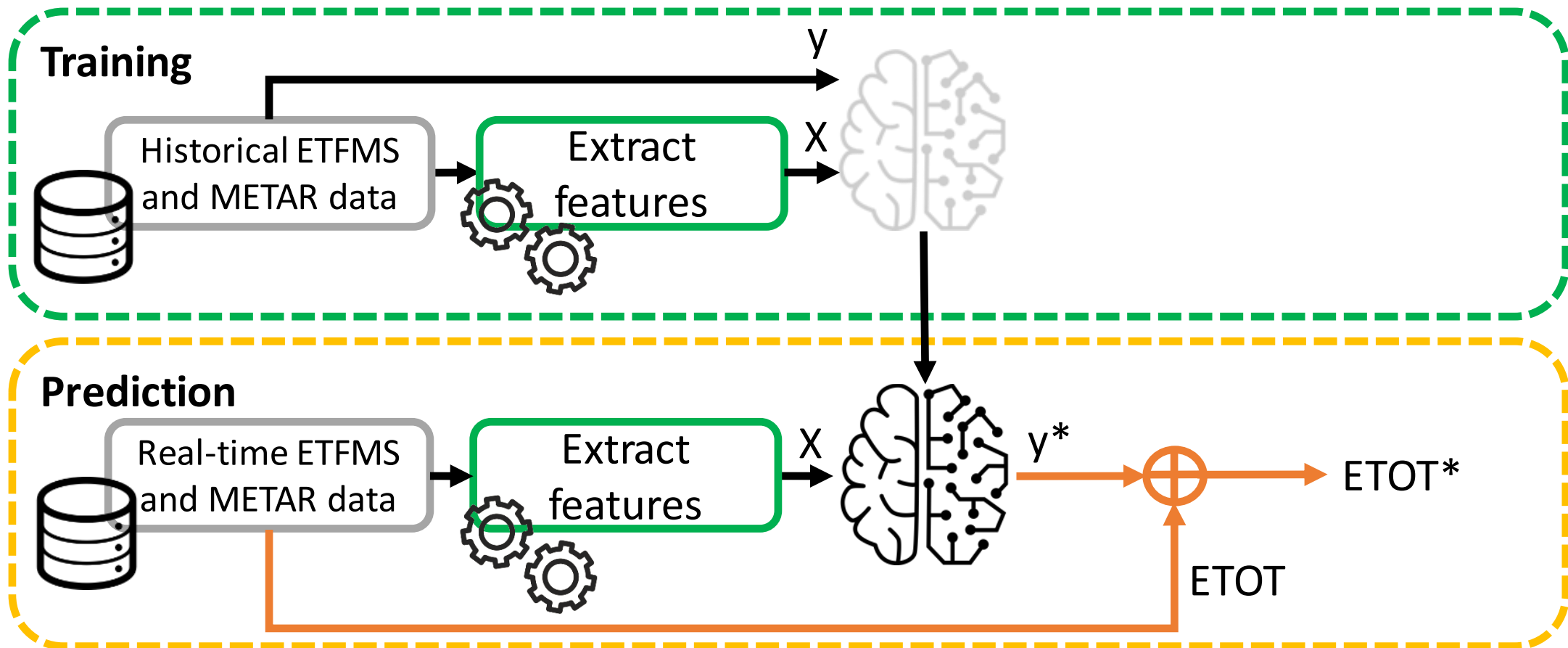
Introduction: Current take-off time predictions



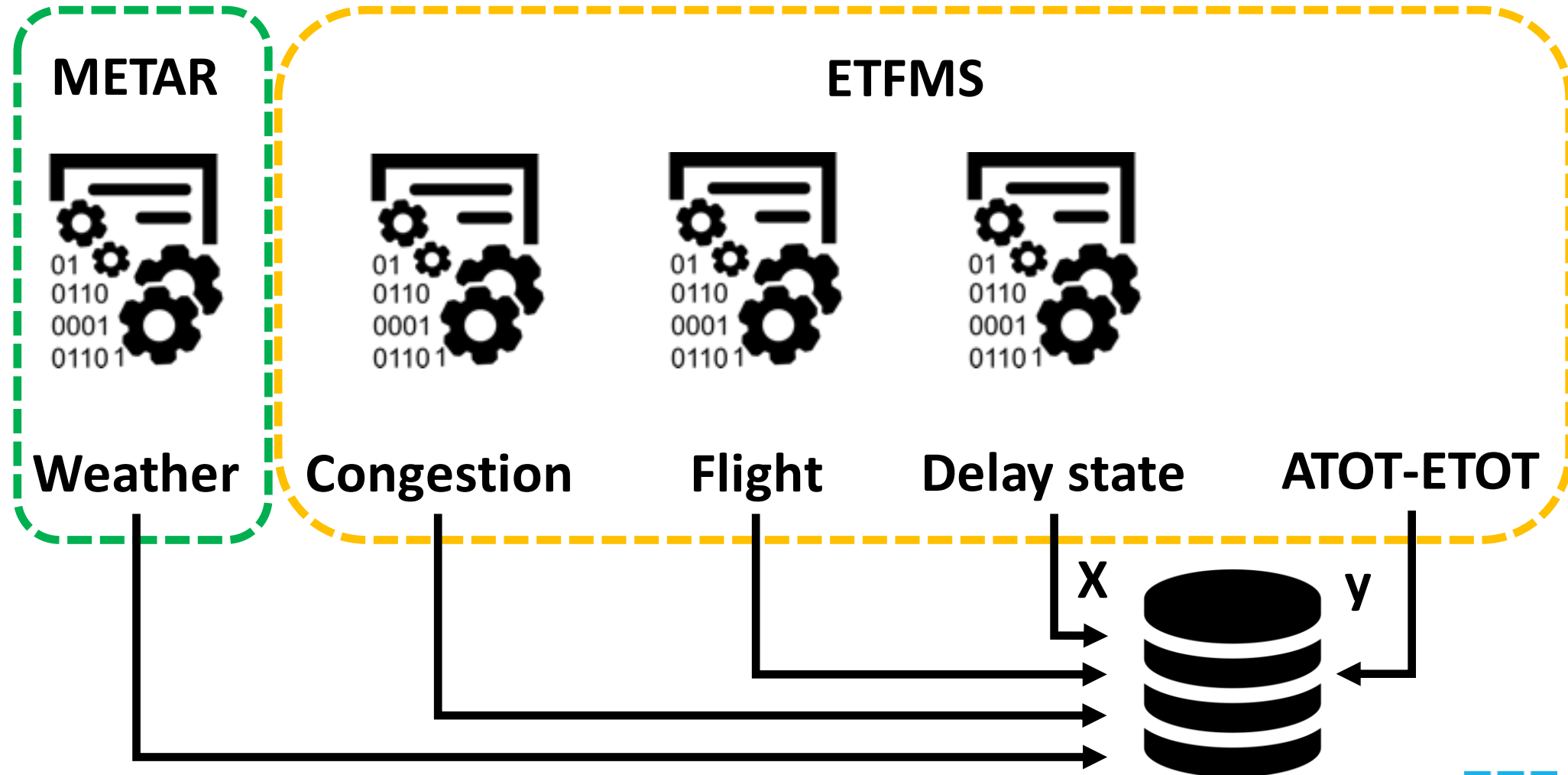
Introduction: AI take-off time predictions



Introduction: AI take-off time predictions



Data set: sources



Data set: ETFMS message and METAR report

ETFMS message

-TIMESTAMP 170701000000 -EVENT CPR -EVENTCLASS MSG -FLTSTATE AA -IFPLID AA65242343 -ARCID SDM6680 -IOBT 2215 -EOBD 170630 -**EOBT 2212** -AOBD 170630 -**AOBT 2208** -ADA 170701 -ATA 0144 -ADEP LEBL -ADES UUWW -MODELTYPE ACT -ARCTYP B738 -IRULES IFR GAT IFPSTART -**TAXITIME 10** ...

METAR report

UATG 010000Z 32004MPS 5000 BR SCT009 M15/M15 Q1020 R32/42//55 NOSIG
RMK QFE767/1022

Data set: Input features

Congestion

Feature <i>j</i>	Type
# of departures at ETOT $\pm$ 15 min	Numerical Dynamic
# of departures at ETOT $\pm$ 30 min	
# of departures at ETOT $\pm$ 60 min	
# of arrivals at ETOT $\pm$ 30 min	
# of arrivals at ETOT $\pm$ 15 min	
# of arrivals at ETOT $\pm$ 30 min	

Delay state

Feature <i>j</i>	Type
# of departures/arrivals with delay in (-30, -15] min	Numerical Dynamic
# of departures/arrivals with (-15, -5] min of delay	
# of departures/arrivals with (-5, 0] min of delay	
# of departures/arrivals with (0, 5] min of delay	
# of departures/arrivals with (5, 15] min of delay	
# of departures/arrivals with (15, 30] min of delay	
# of departures/arrivals with (30, 60] min of delay	

Weather

Feature <i>j</i>	Type
Temperature	Numerical
Visibility	
Ceiling	
Wind direction	
Wind speed	
Wind gust	Dynamic
Precipitation	
Cloud cover	Categorical
Cloud type	

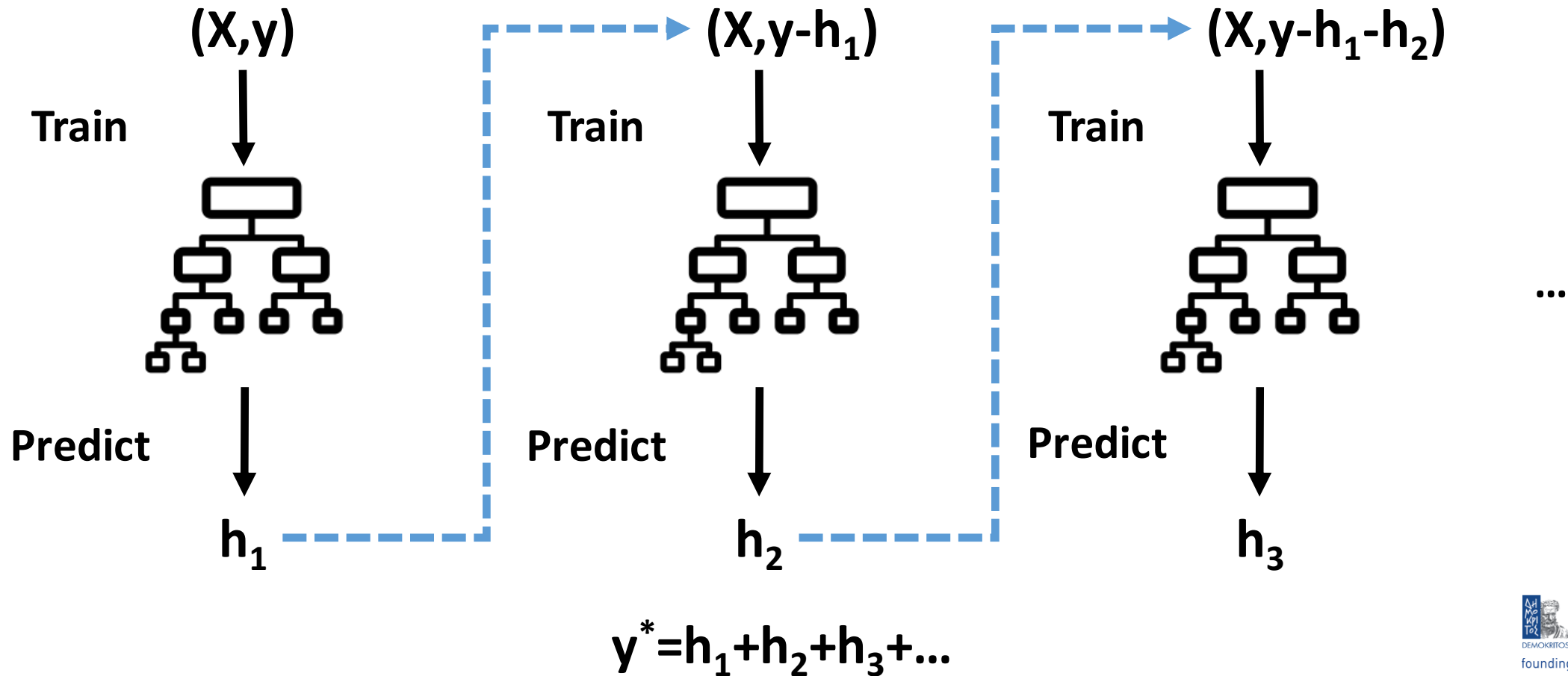
Calendar

Feature <i>j</i>	Type
Hour of the day	Categorical Static
Day of the week	
Month of the year	

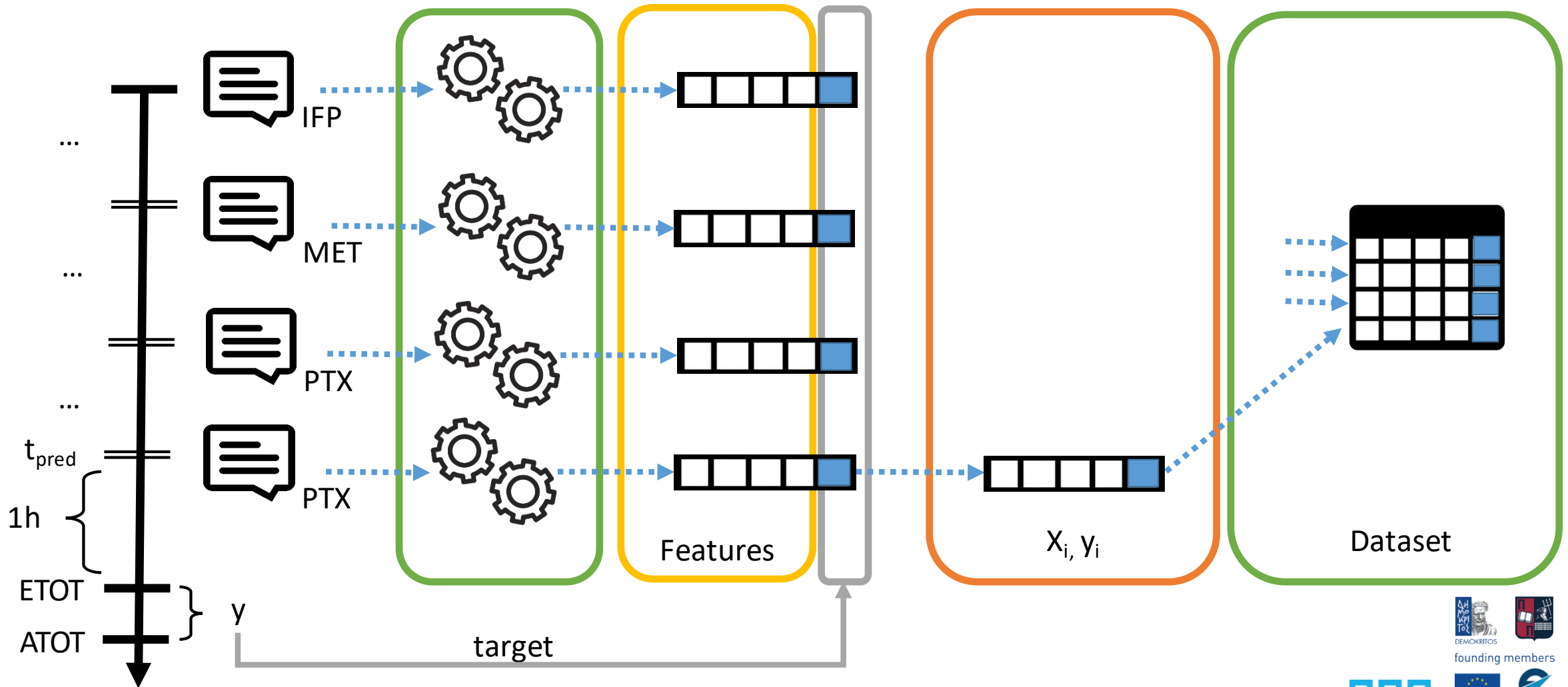
Flight

Feature <i>j</i>	Type
Available turn-around time	Numerical Dynamic
Available turn-around time for the next leg	
Duration of the flight	
Duration of the previous leg	
ATFM delay	
Time to EOBT	
EOBT delay w.r.t IFP	
Target Off-Block Time (TOBT) - EOBT	
Target Start-up Approval Time (TSAT) - EOBT	
Time from IFP	
Time from airframe allocation	
Taxi-in time	
Time to take-off for the previous leg	
Time from previous leg message	
Delay of the previous leg w.r.t IFP	
Aircraft type	Categorical
Aircraft operator of the previous leg	
Aircraft operator of the next leg	
Departure airport of the previous leg	
Destination airport of the next leg	
ATM flight status	
ATM flight status of the previous leg	
Event that triggered the message	
Event that triggered the previous leg message	
Last letter of the SID	
Traffic volume of most penalising regulation	Static
Departure airport	
Destination airport	
Country of departure	
Region of departure	
Alliance of the airline	
Aircraft operator	

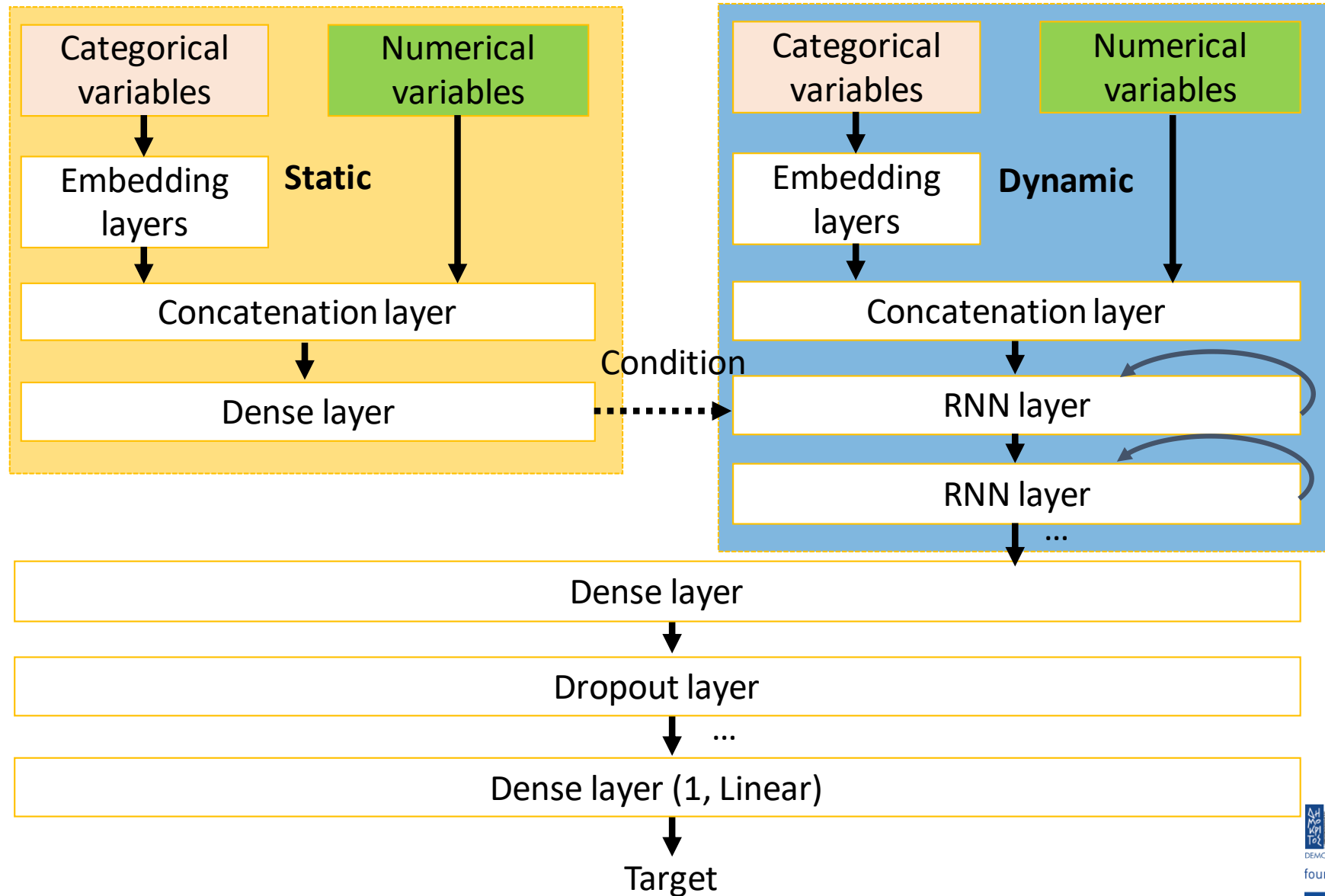
Models: lightGBM



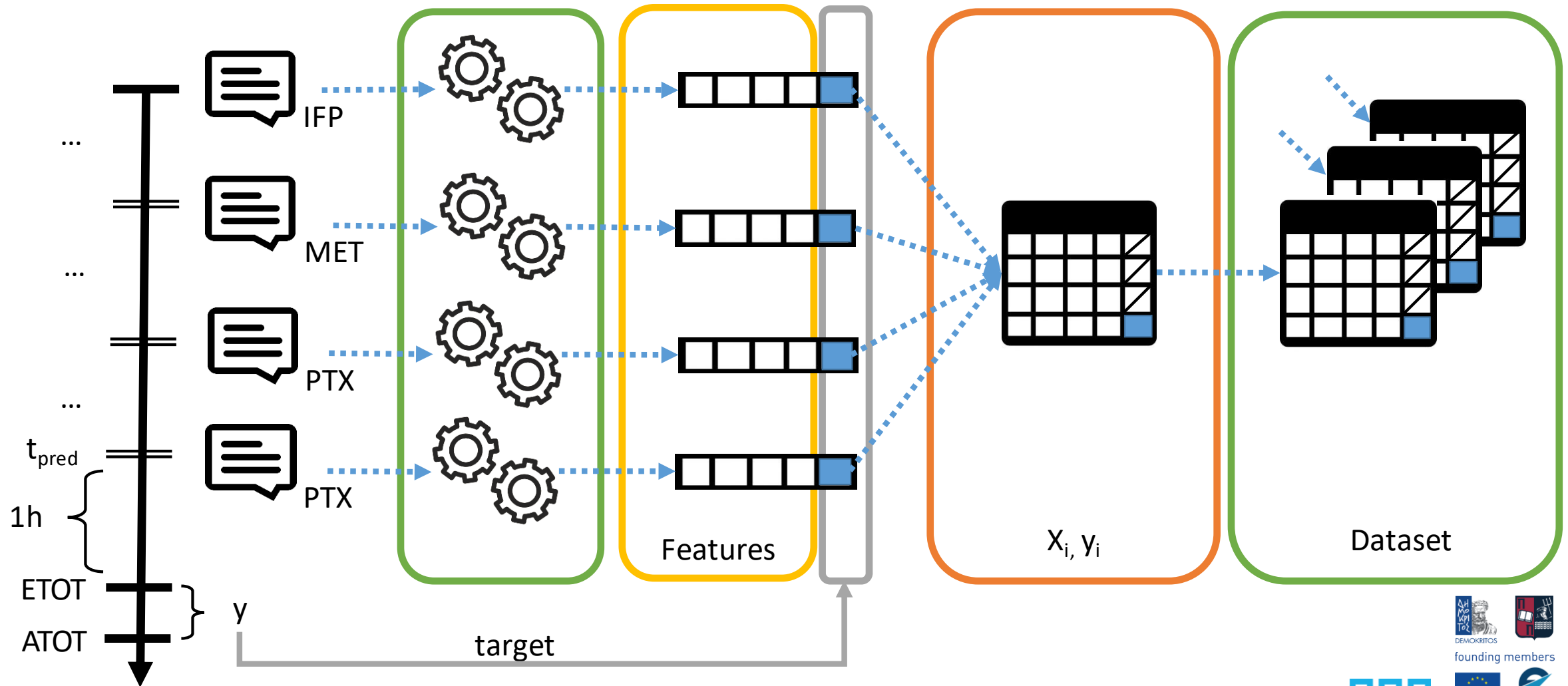
Models: lightGBM



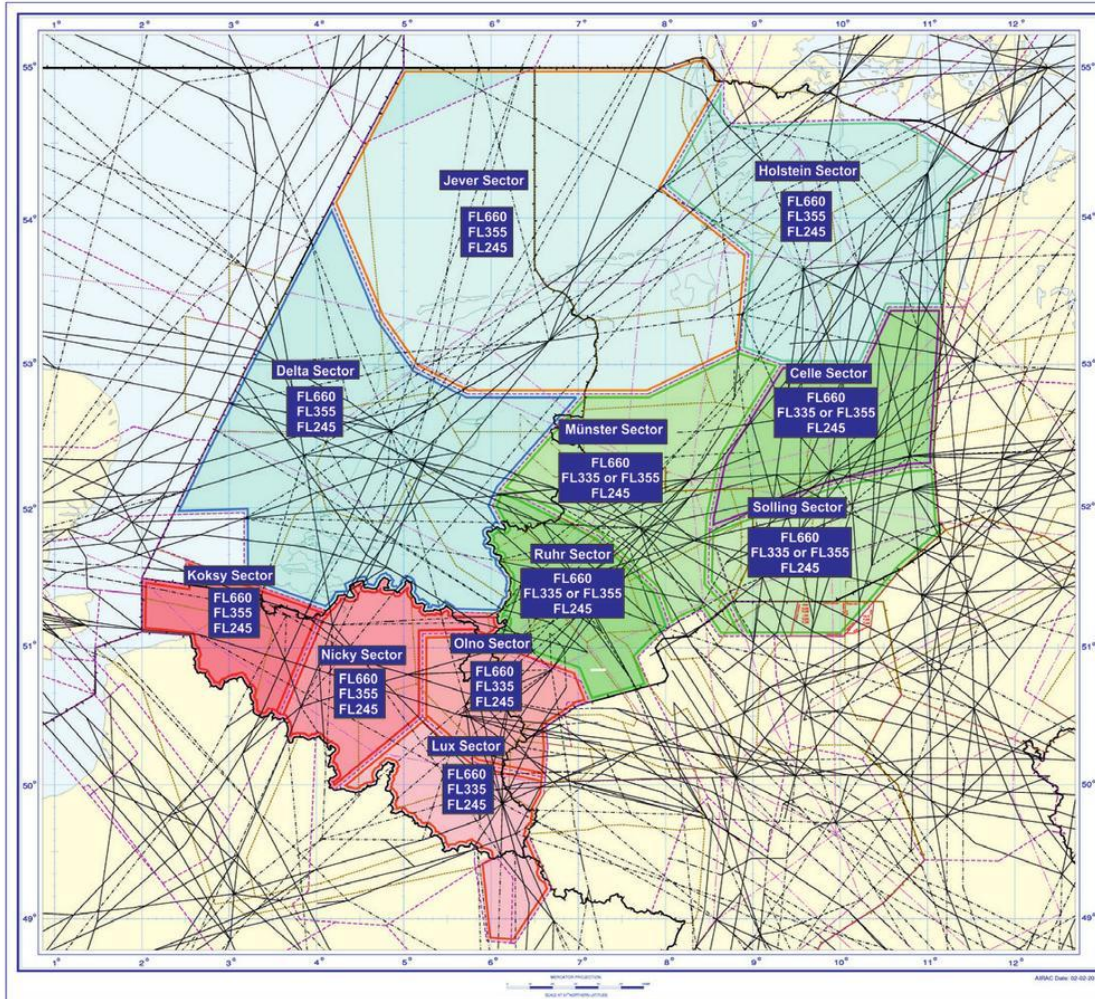
Models: RNN



Models: RNN



Setup of the experiment



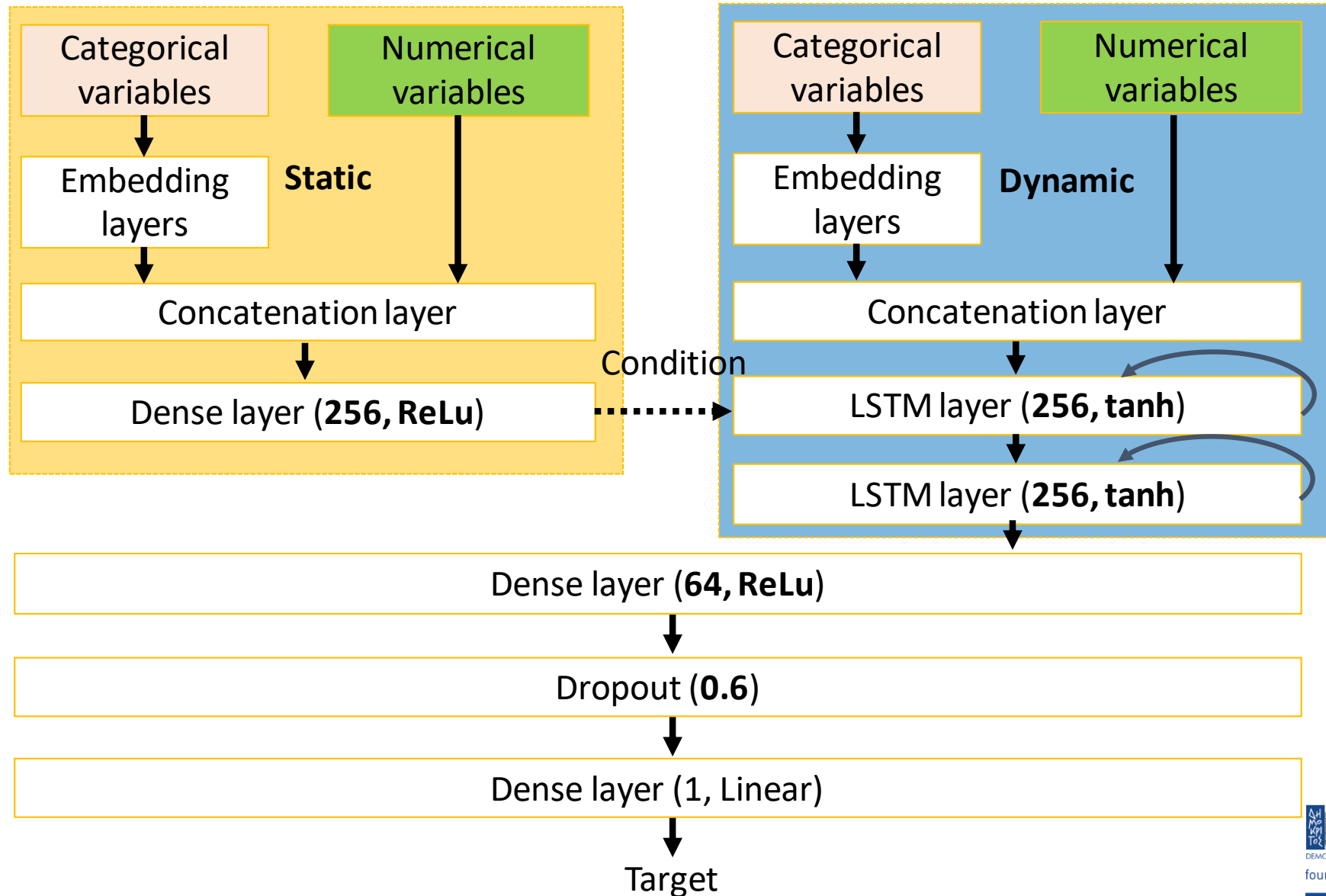
- Only flights **crossing MUAC** airspace
- **January of 2016 to December of 2018**
- After removing outliers, around **5M** flights
- **70%** of the flights for **training** the models
- **20%** of the flights for **testing** the performance on unseen data
- **10%** of the flights for **validation** (early-stopping + parameters tuning)

Results: lightGBM hyperparameters

hyperparameter	value
max_bin	512
num_leaves	512
num_trees	512
max_depth	32
learning_rate	0.05

Results:

RNN hyperparameters

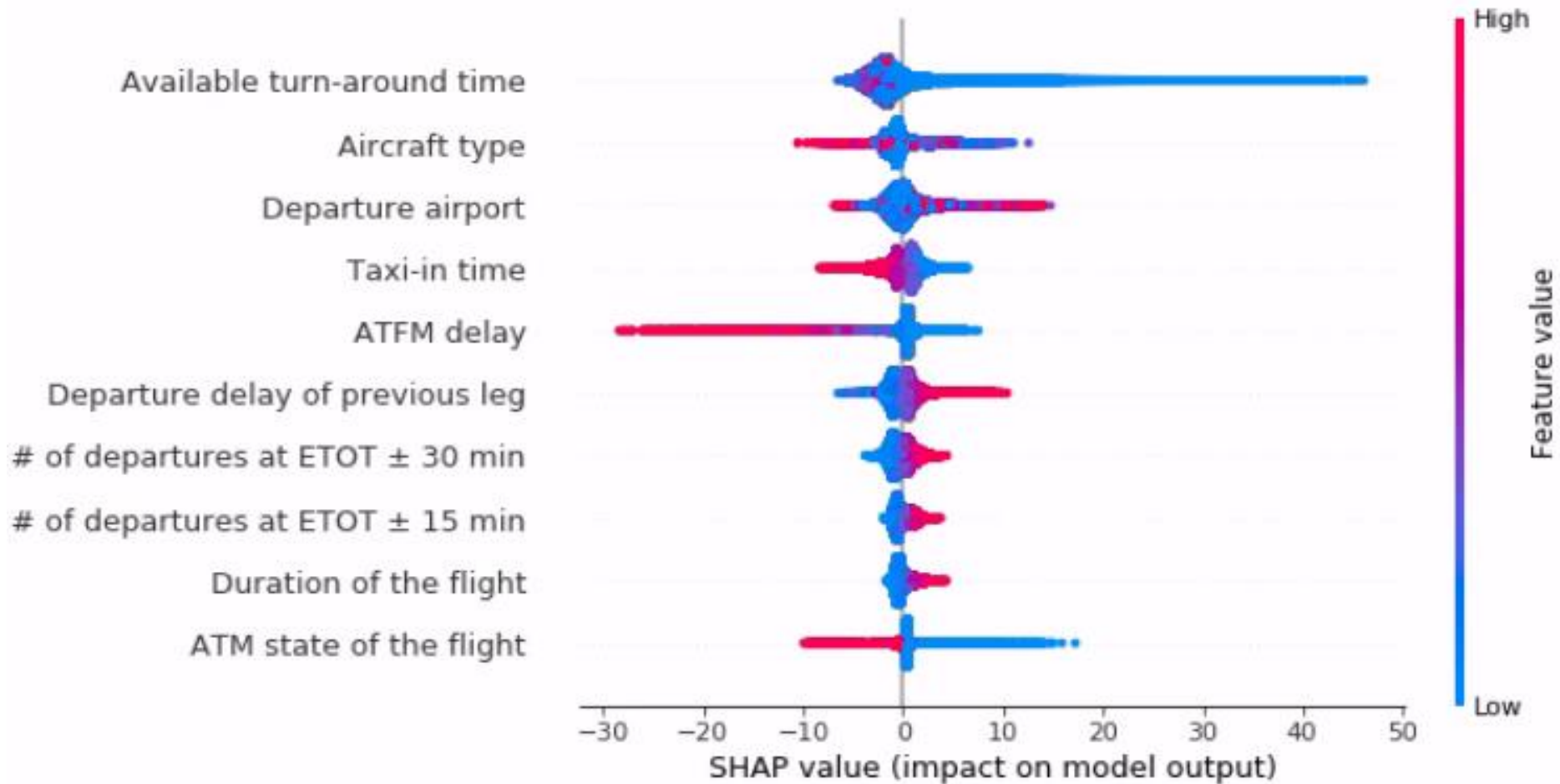


Results: performance metrics on test set

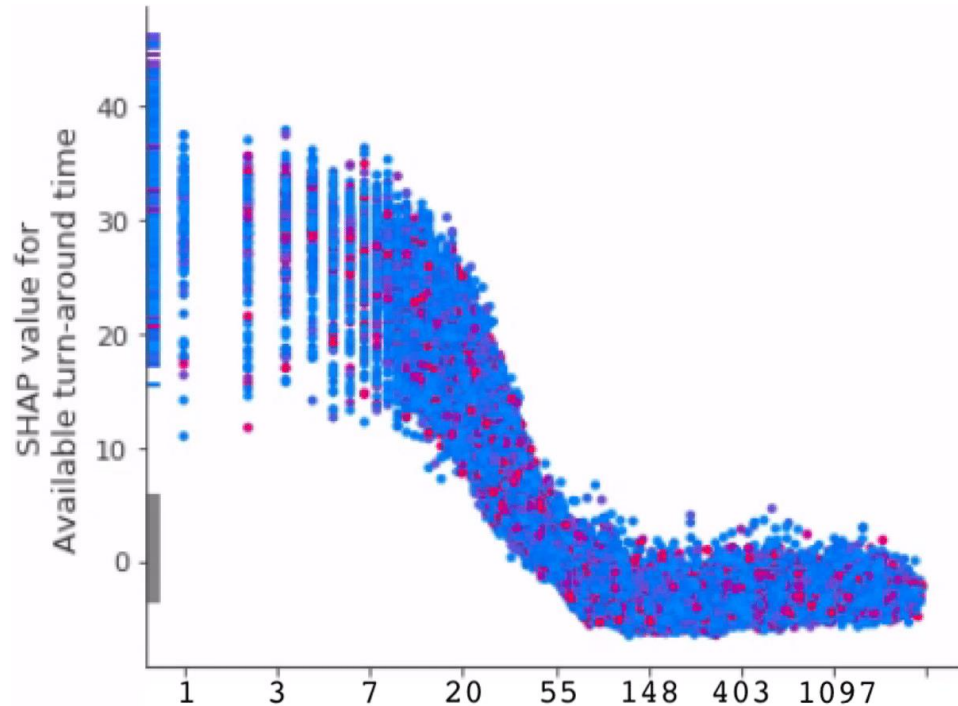
metric	ETFMS	lightGBM	RNN
Mean Absolute Value (MAE)	10 min 10 s	7 min 8 s	7 min 22 s
Standard deviation (STD)	10 min 57 s	8 min	8 min 19 s
1 st quartile (Q1)	3 min	2 min 11 s	2 min 18 s
2 nd quartile (median)	6 min 37 s	4 min 50 s	5 min 3 s
3 rd quartile (Q3)	13 min	9 min 5 s	9 min 15 s

30% of MAE and STD reduction with respect to ETFMS

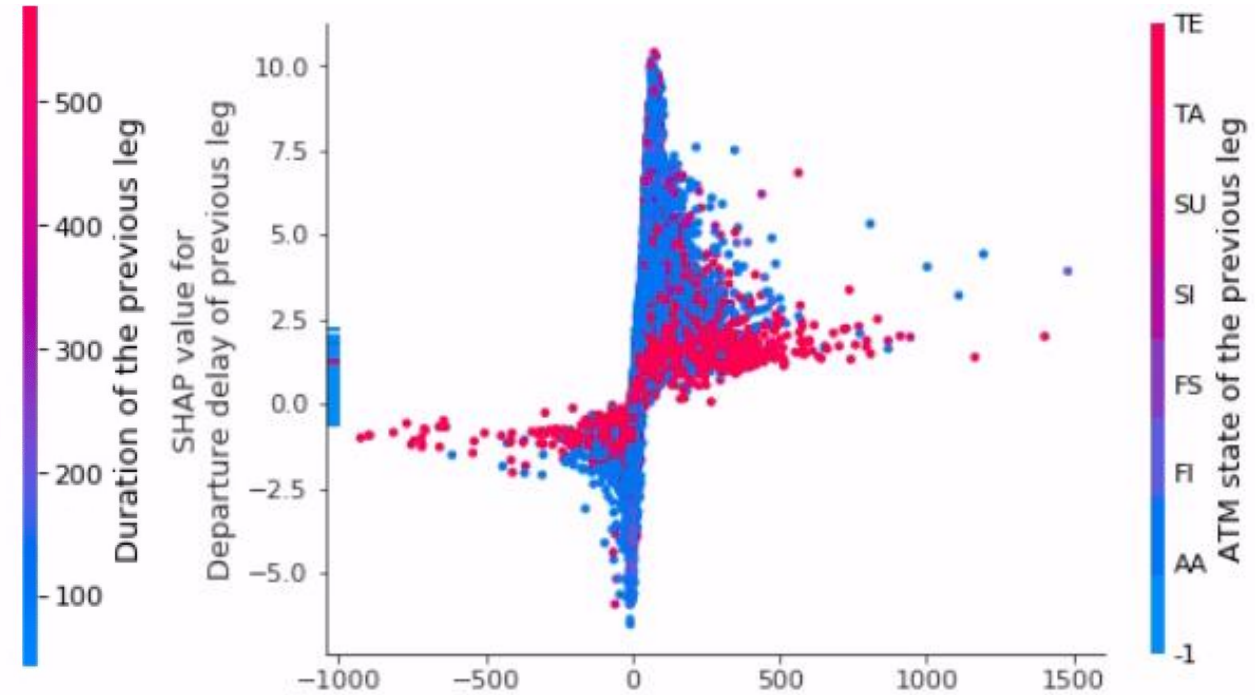
Results: Features importance



Results: Features dependence – Flight

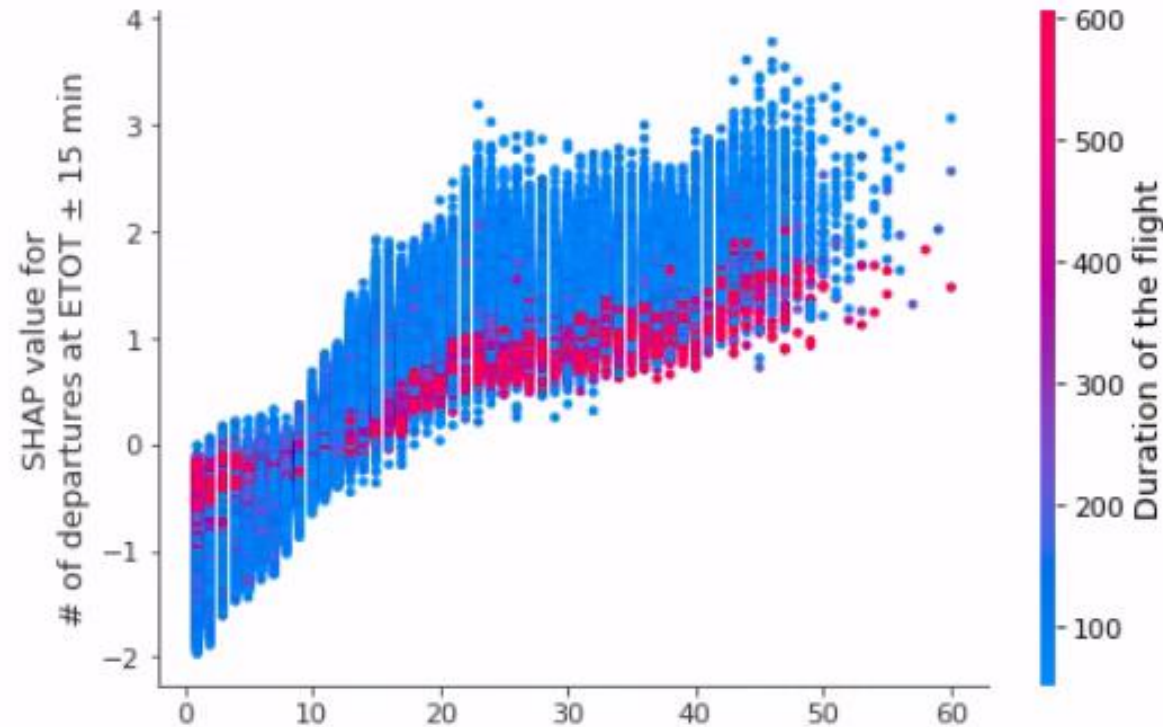


Available turn-around time



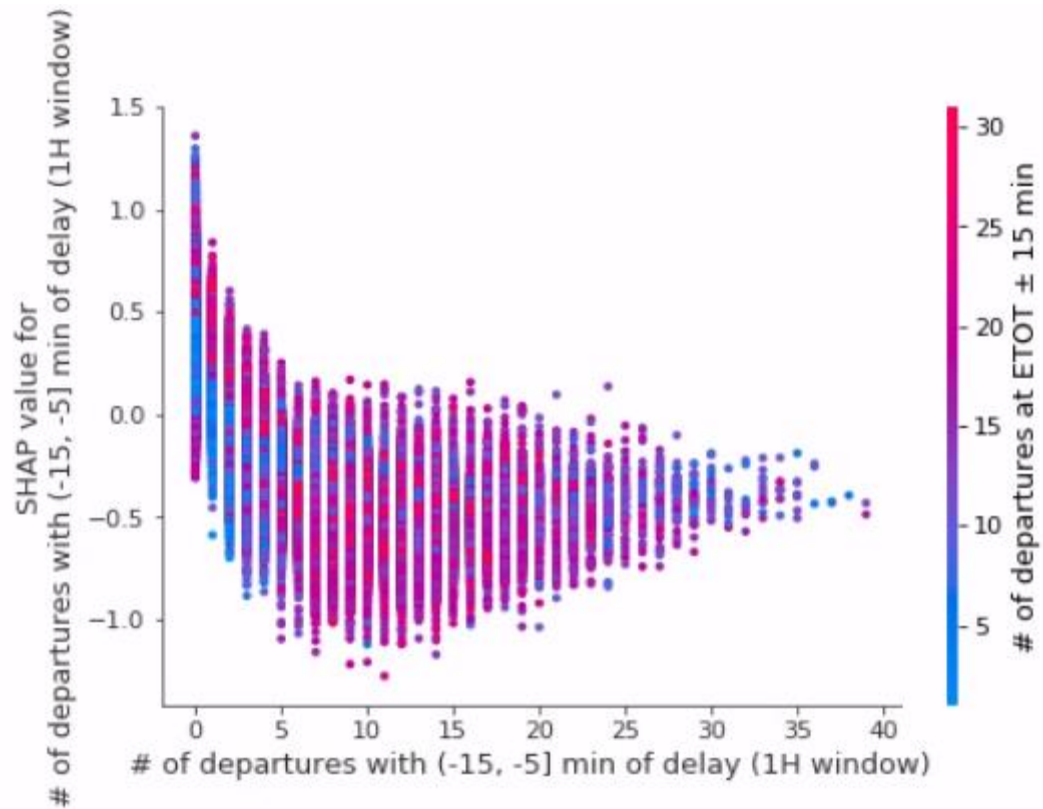
Departure delay of previous leg

Results: Features dependence – Congestion

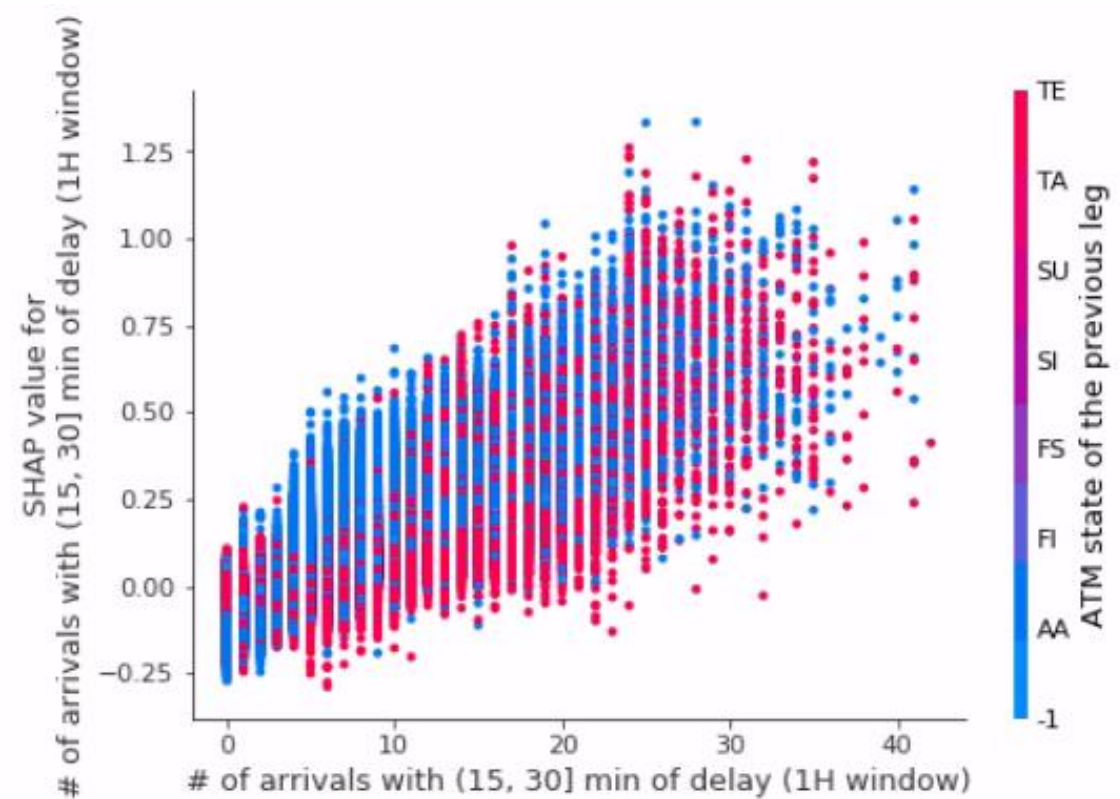


Number of departures at ETOT +- 15 minutes

Results: Features dependence – Delay state

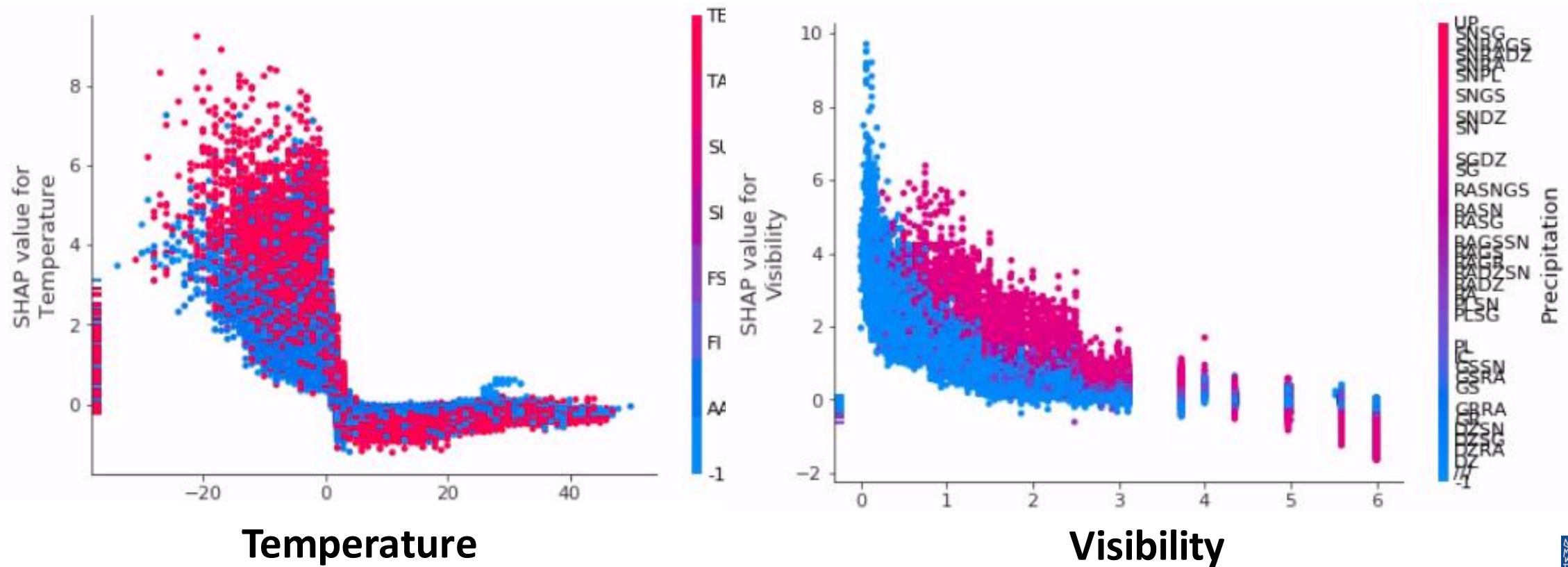


Early departures in the last hour



Late arrivals in the last hour

Results: Features dependence – Weather



Conclusions

- **Machine Learning (ML)** can improve the predictability of take-off times by **30% one hour before EOBT**, if compared to the **ETFMS** predictions
- The information of the whole sequence of messages for each flight **does not add clear benefit** to the prediction, that the ANN cannot extract it, or that sequential information is already included
- There are still a lot of **missing factors** leading to **mismatches between ETOT and ATOT** that have not been considered (airline and airport data)
- The model still predicts from the point of view of a **single flight**
- Model needs to be extended to **all look-ahead times**, from IFP to ATOT

Thank you! **Efharisto !**