



# Trajectory prediction (data-driven)

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(FPL-EN105-IS
-B763H-6344M:SRVWX-H2L2V2G1
-ZZZZ1200
-N0400F100 DENJUT UL610 LAM UL10 BPK UN601 LESTA UPS
MMKLM062F320 NATB YAYN0464F320 N188B YRIN0462F340 DCT NOTAP
DCT TVC PIRMS
-KORD0700 KATL
-STS(ATFMA MARS FLTK PEN A1C3L1 NAVIGBAS SBAS DATA)
SPECIFIC DESIGNATORS (P) ADDITIONAL INFO DEPMALAHIDE
SSZ7N000R09W (P) 880622 TYPZF15 SPB DE NTM0130
CANCEL EBB0ZMFP PERA (A) EDW RMK(PRESSURISATION PROB
UNABLE ABOVE F120)
    
```

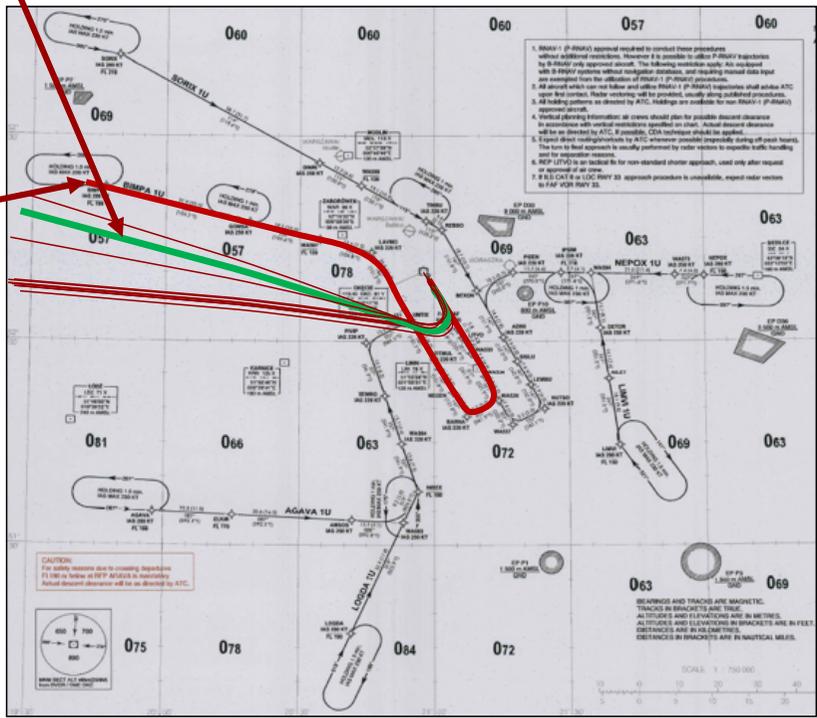
**Model-based  
Trajectory  
prediction**



**Surveillance  
Data**

**DataCRON  
Trajectory  
prediction**

**Historical data  
+ context data**



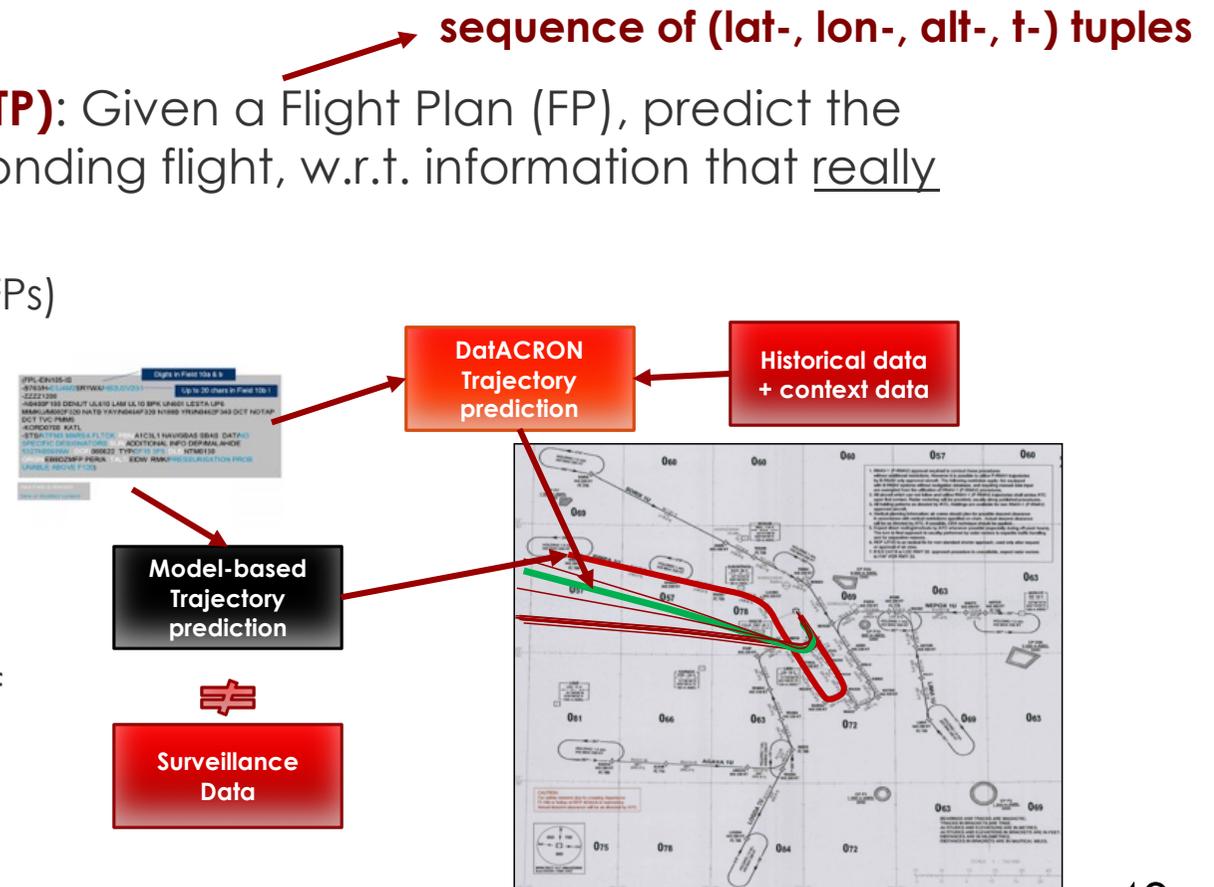
# Trajectory prediction (data-driven)

- Problem definition:

**pre-flight Trajectory Prediction (TP):** Given a Flight Plan (FP), predict the actual trajectory of the corresponding flight, w.r.t. information that really matters

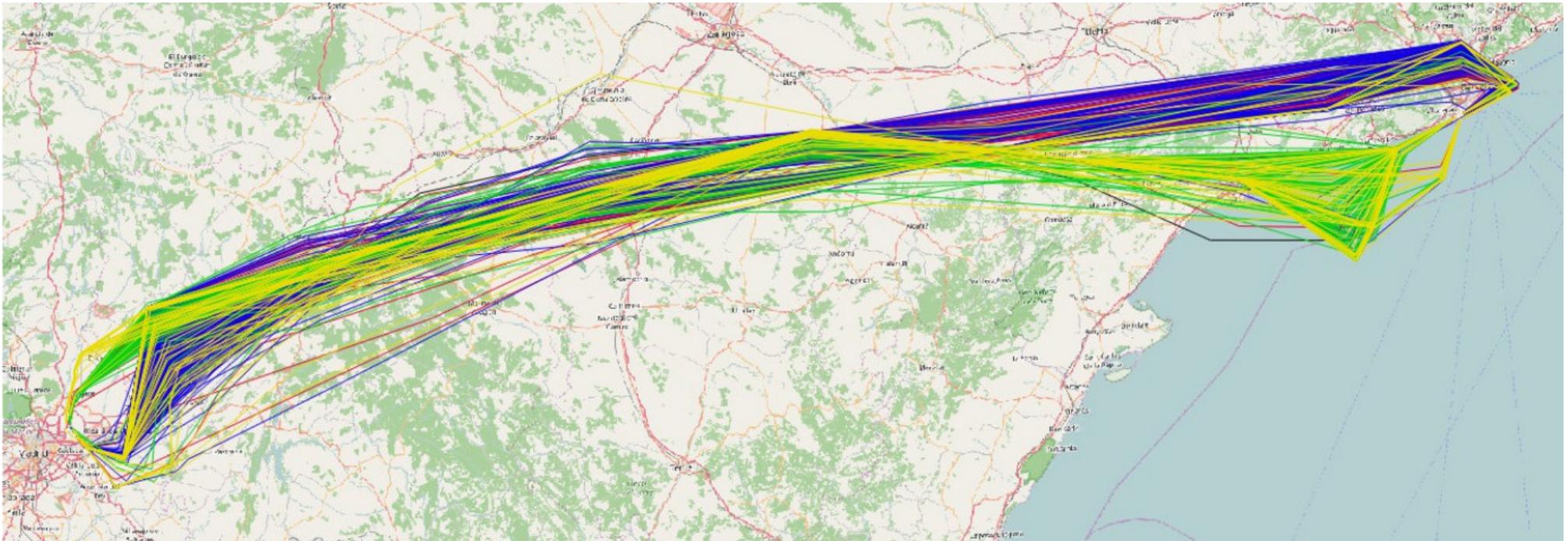
- Historical data (actual flights and FPs)
- Current and forecasted meteo,
- Predicted air-space traffic,
- etc.

- Offline problem – before takeoff



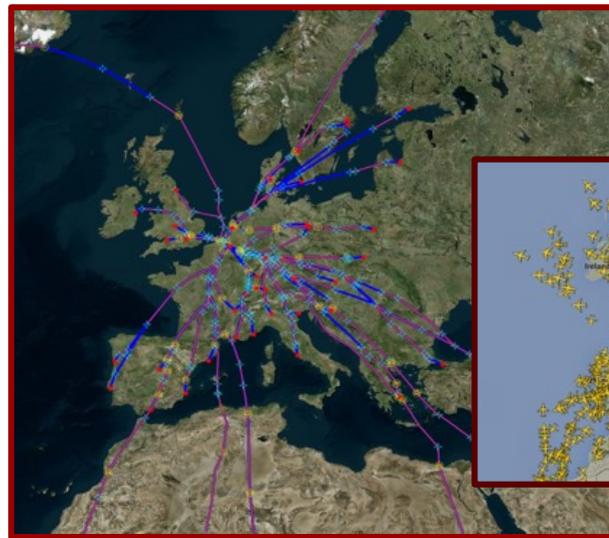
# Experimental dataset

- Spain (Madrid-Barcelona flights), April 2016



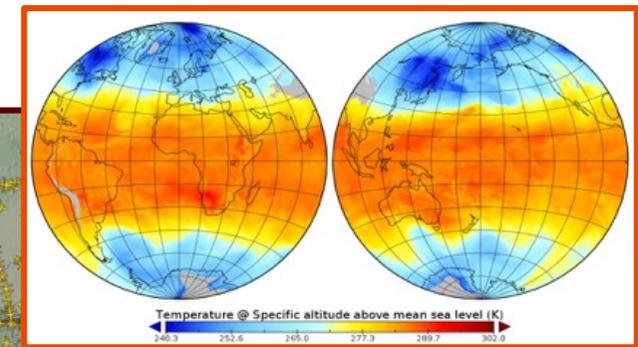
# Handling big data

- DataSets:
  - Initial Flight Plans
  - Surveillance data
  - Weather live data and forecasts
  - Other context data



EBBR Outbound Flight Plans for a 2 hour timeslot

ADS-B Surveillance traffic

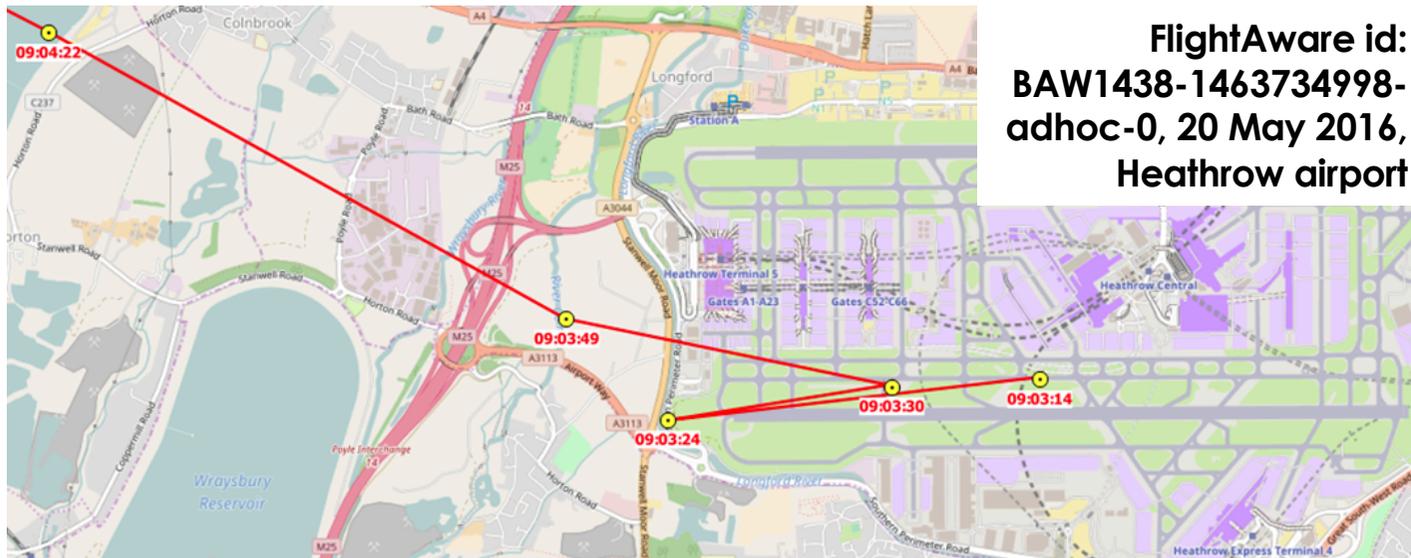


European Sector static information

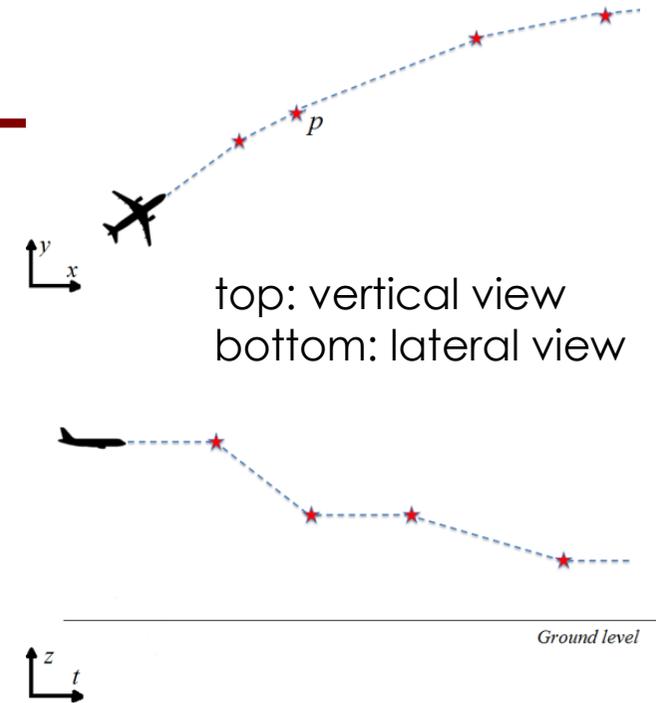
# Handling big data (cont.)

- Challenges: **identify critical points**, detect and eliminate noise, fuse information from different sources, etc.

... all to be performed **online!**

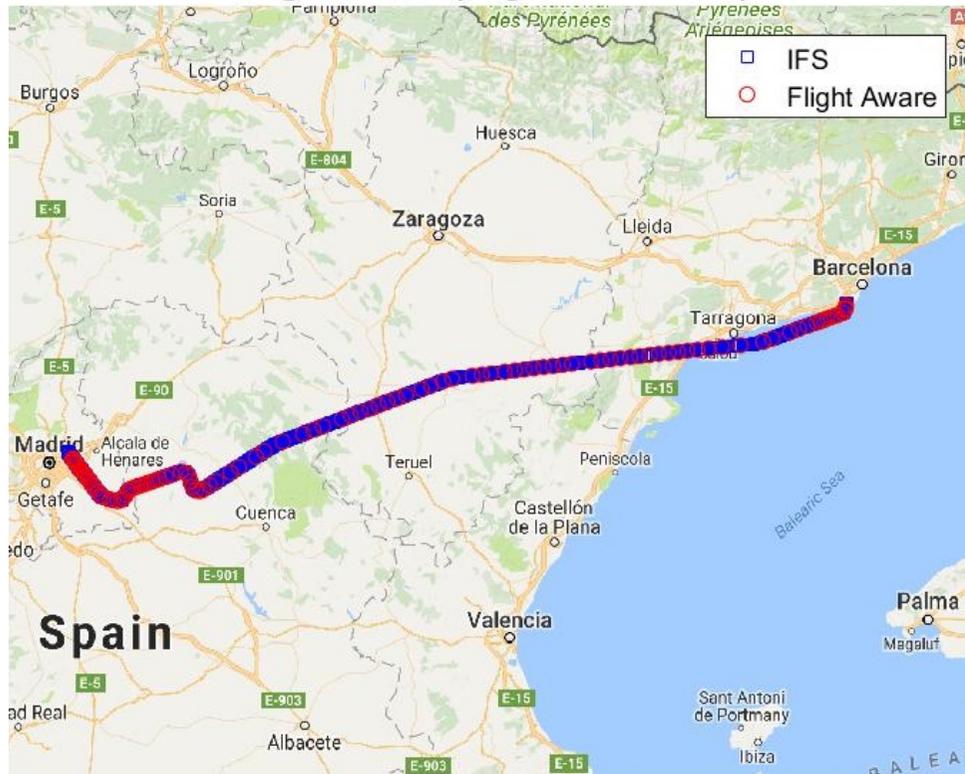


FlightAware id:  
BAW1438-1463734998-  
adhoc-0, 20 May 2016,  
Heathrow airport

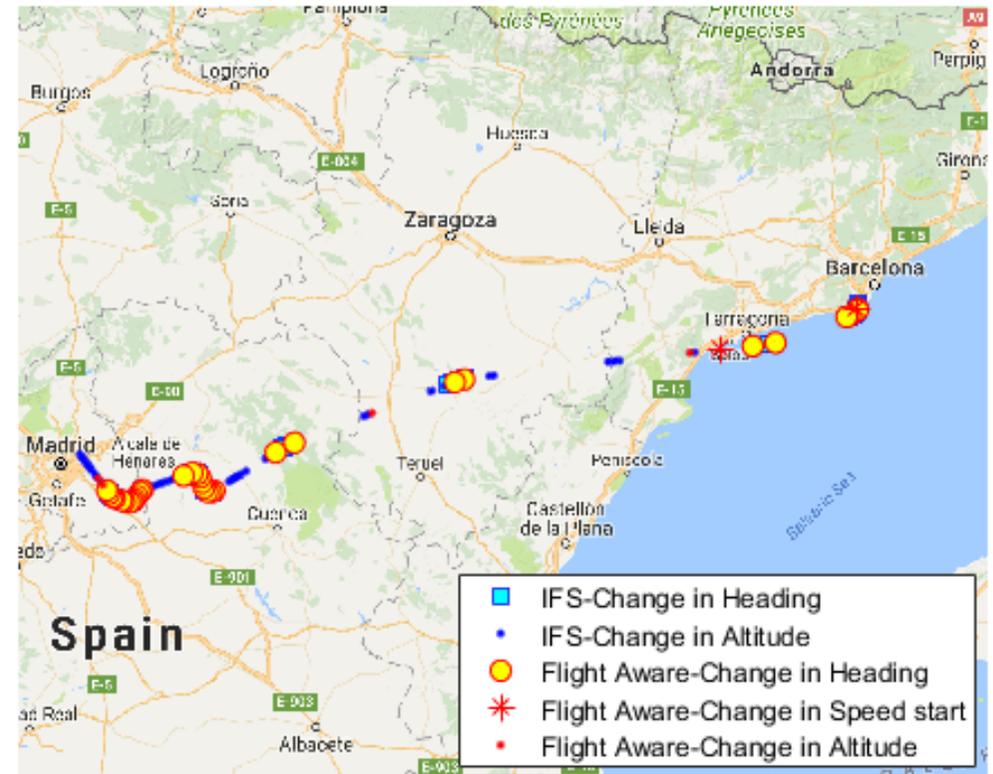


# Handling big data (cont.)

Original track (Flight id: IBE1925)



Synopsis (Flight id: IBE1925)



# Data-driven trajectory prediction

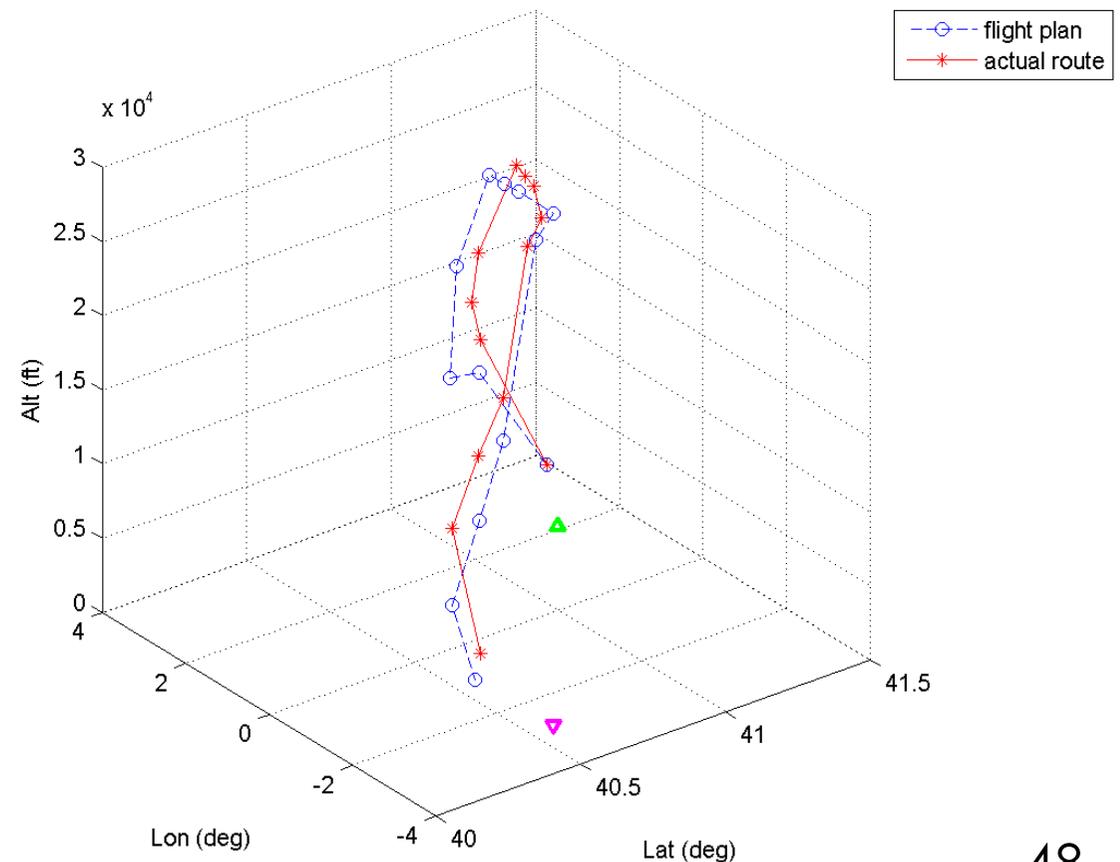
(Georgiou et al. 2019)

## Method sketch:

Input: Flight plans, actual routes, local weather, aircraft type, etc.

1. Past enriched trajectories are **Clustered**; medoids of clusters ('representatives') are also produced
2. A **Predictive Model** (PM) is built for each cluster
3. For each new flight plan FP, the **k-closest matches** (PMs) are found
4. Output: top-k PMs w.r.t. query FP

Flight (7573900): from LEBL (id:2248) to LEMD (is:2200) on 30-Apr-2016 06:45:56  
13 samples in 3.083000e+03 secs (rate: 1/[100...630])



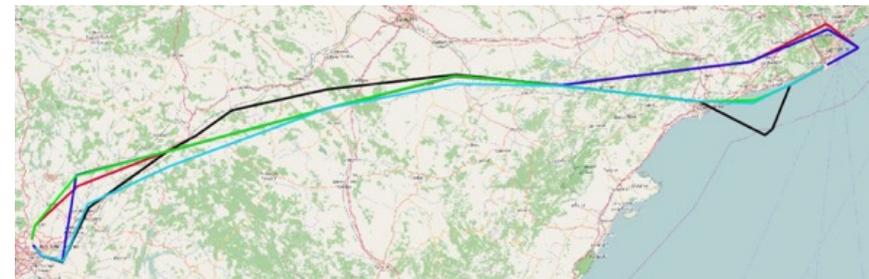
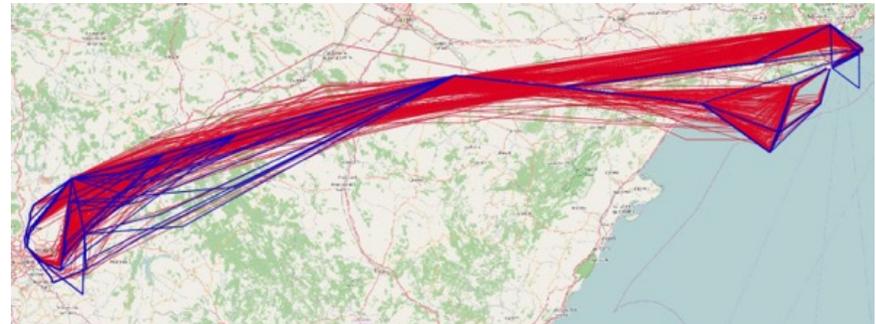
# Data-driven trajectory prediction (cont.)

(Georgiou et al. 2019)

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# Data-driven trajectory prediction (cont.)

(Georgiou et al. 2019)

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Input: Flight plans, actual routes, local weather, aircraft type, etc.

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