



Flight trajectory data analytics for characterization of air traffic performance

McWillian de Oliveira – Ph.D. Student
Prof Dr Mayara Condé Rocha Murça - Advisor

Brazil, August 20 and 21

Workshop ITA-MIT on big data analytics for air transportation

Contents

1. Introduction
2. Methodology
3. Results and discussion
4. Summary and next steps

Introduction

- Air Traffic Management (ATM) - key element of air transportation

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safety, efficiency and
environmental impact

Introduction

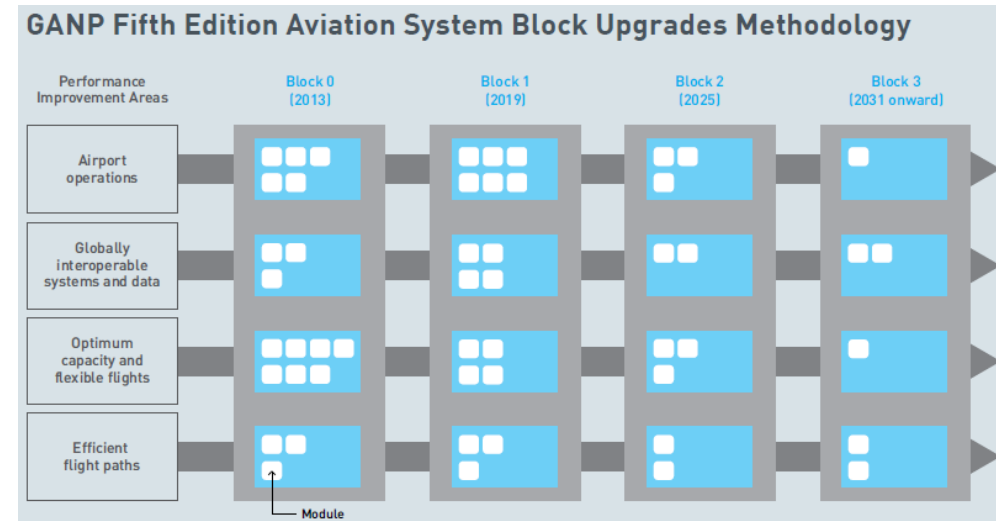
- Air Traffic Management (ATM) - key element of air transportation
- Global air traffic has doubled once every 15 years since 1977
- Demand will double by 2035, reaching 7.2 billion passengers

safety, efficiency and
environmental impact

Introduction

- Air Traffic Management (ATM) - key element of air transportation
- Global air traffic has doubled once every 15 years since 1977
- Demand will double by 2035, reaching 7.2 billion passengers
- Technological and operational improvements for modernization of the ATM system have become necessary

safety, efficiency and environmental impact



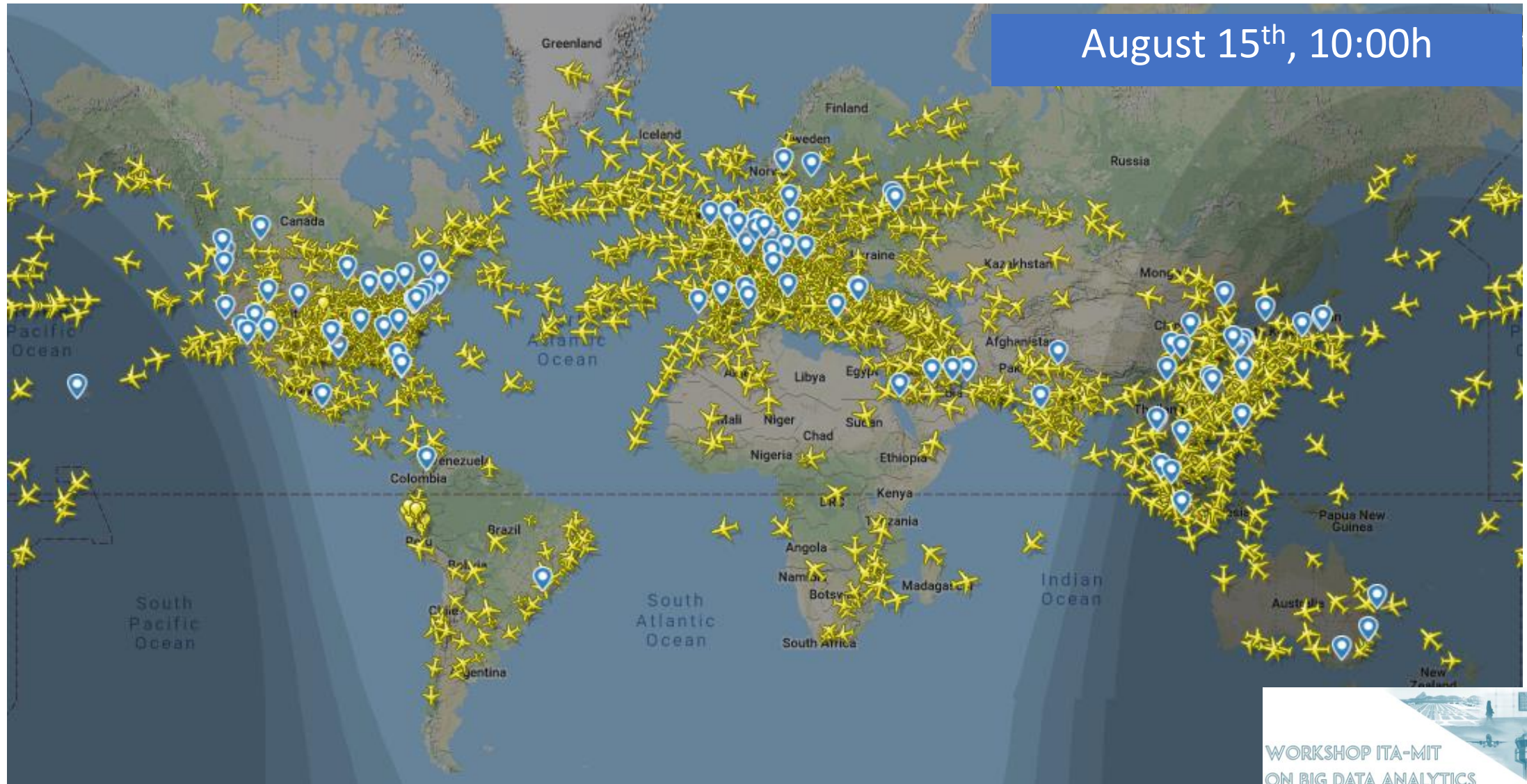
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safety, efficiency and
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Introduction

August 15th, 10:00h

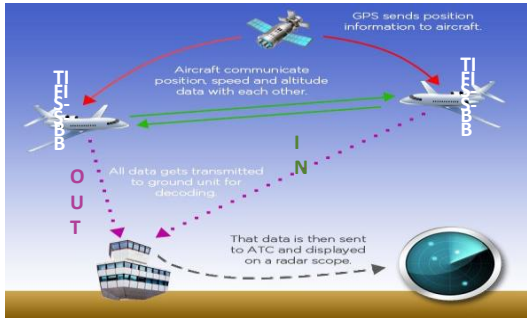


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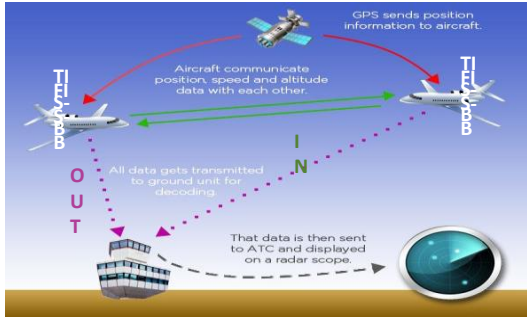
Introduction



New technologies and
operational procedures



Introduction



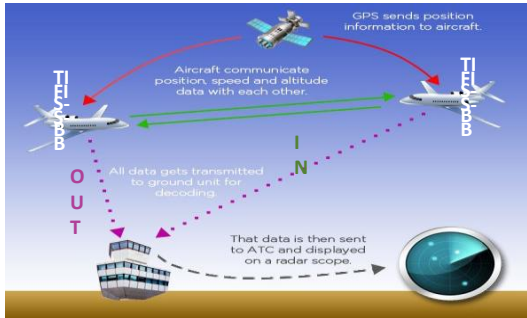
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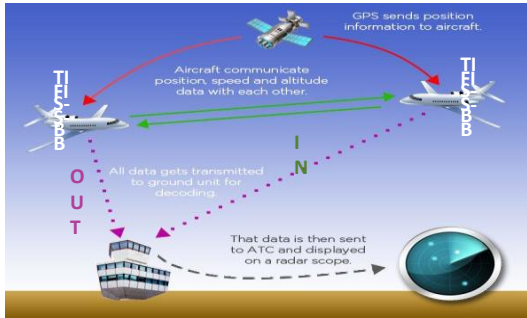
New technologies and operational procedures



Leveraging **operational data** is also key to improve ATM and increase the performance of air traffic operations



Introduction



New technologies and operational procedures



Leveraging **operational data** is also key to improve ATM and increase the performance of air traffic operations



Flight trajectory data analytics for characterization of air traffic performance

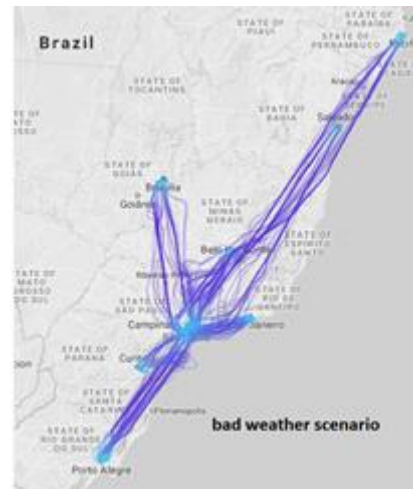
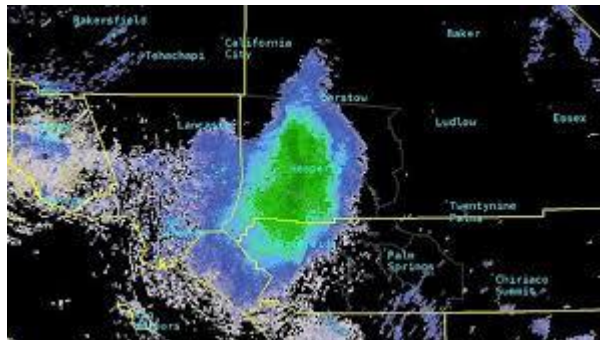
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Introduction

Motivation

- Analytics techniques - assessing the air traffic performance at different dimensions and better understanding how this performance is affected by various operational factors

$$HTE_{kt} = \beta_1 DEMAND_{kt} + \beta_2 LIFR_{kt} + \beta_3 WX_{kt} + \beta_4 GUSTS_{kt} + \beta_5 MIT_{kt} + \beta_6 NC_{kt} + \beta_7 k_t + u_{kt}$$

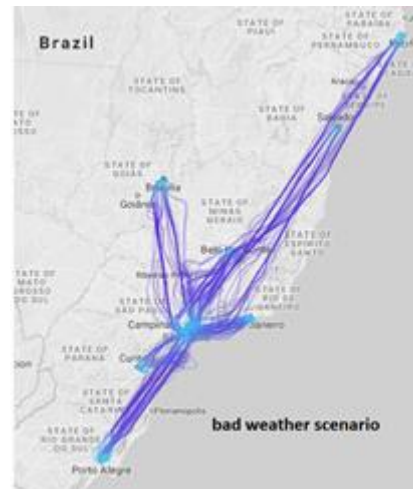
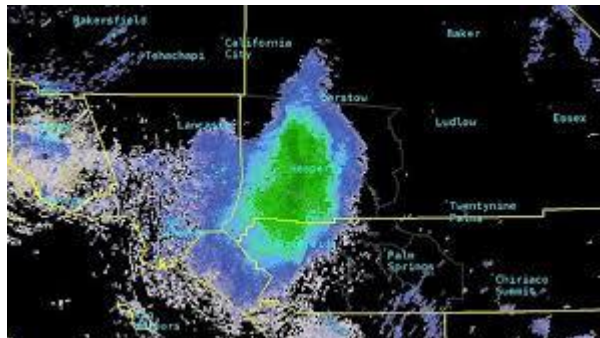


Introduction

Motivation

- Analytics techniques - assessing the air traffic performance at different dimensions and better understanding how this performance is affected by various operational factors
- Sources of inefficiencies / new models and tools - better predict and control the performance of the system

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Introduction

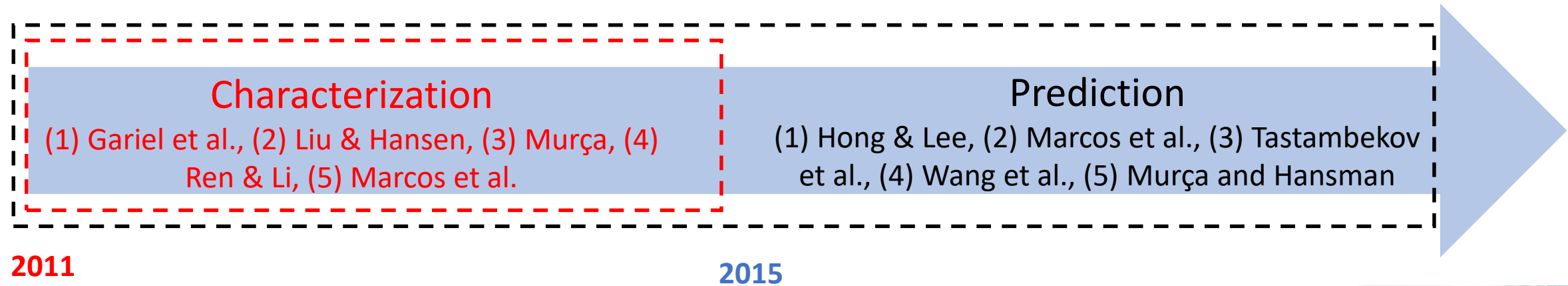
Literature review

- Trajectory data mining - variety of domains (vehicles, people, animals etc)

Introduction

Literature review

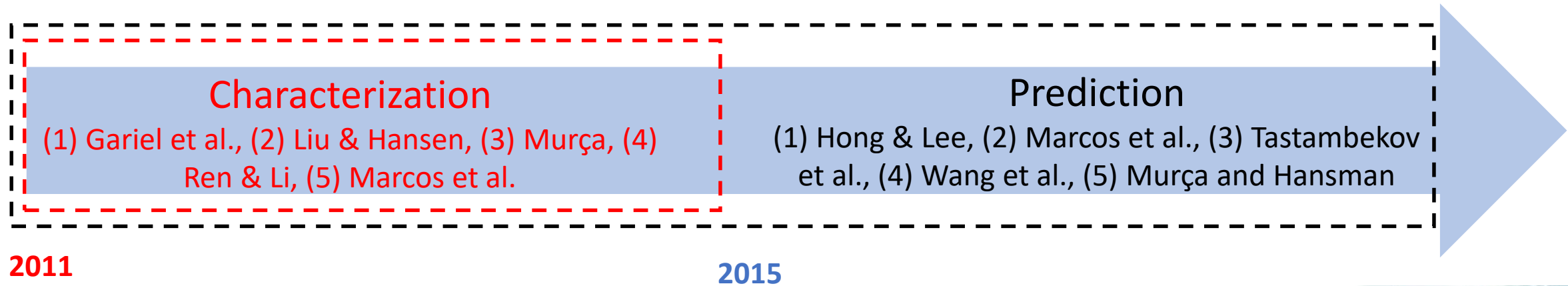
- Trajectory data mining - variety of domains (vehicles, people, animals etc)



Introduction

Literature review

- Trajectory data mining - variety of domains (vehicles, people, animals etc)
- Previous work on flight trajectory data analytics has focused on a single flight phase
- Air traffic behavior and performance dependencies between different scales are not explored



Methodology

Data description

Main dataset

- The raw dataset - 44 days (2017)
- FlightRadar24 tracking service
- flight ID timestamp, latitude, longitude, altitude, speed, origin airport, destination airport and aircraft type

Complementary datasets

- Meteorological Weather Report (METAR)
- Historical traffic management initiatives from Brazilian Air Navigation Management Center (CGNA)

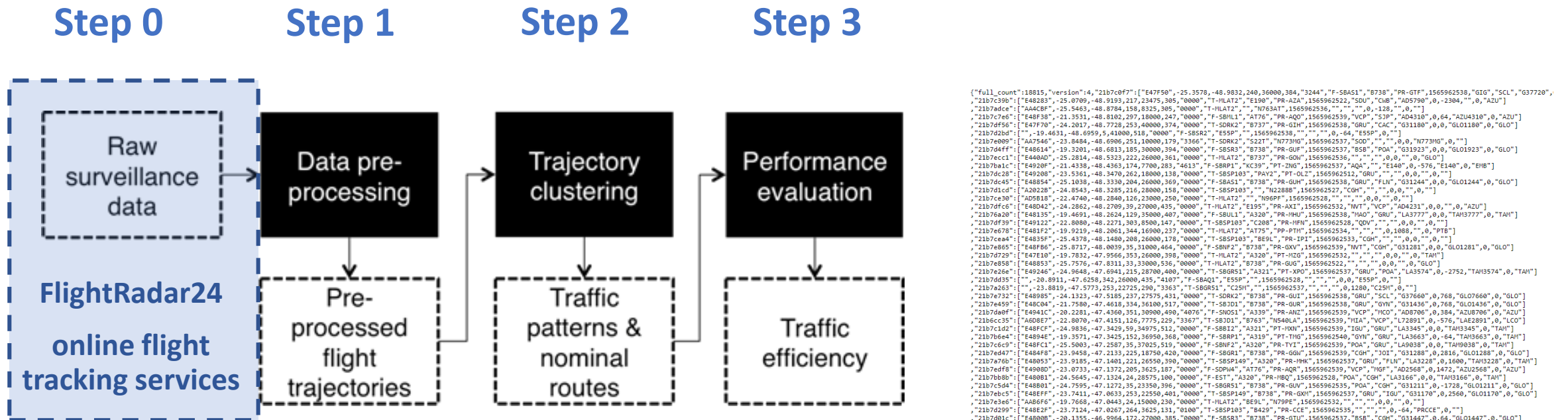


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Methodology

Air traffic performance characterization



FlightRadar24
online flight
tracking services

Automatic extraction of data



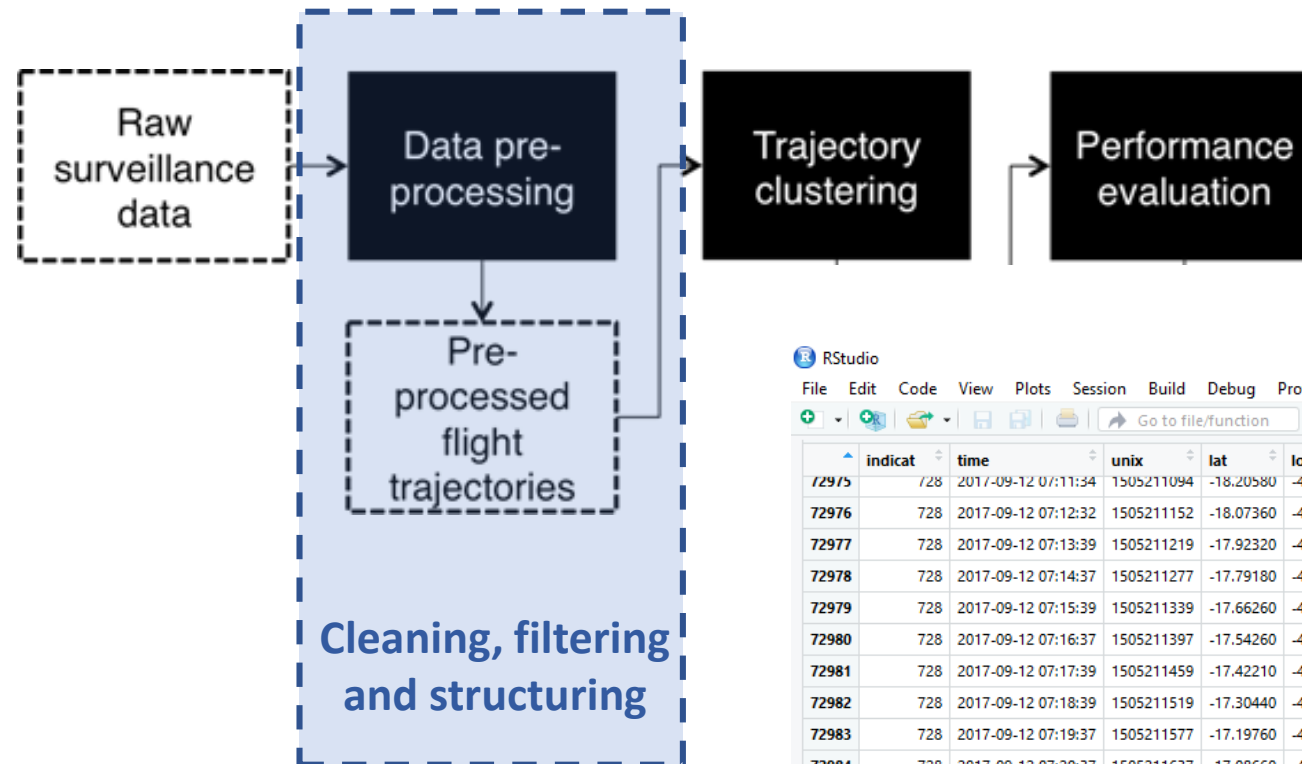
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Methodology

Air traffic performance characterization

Step 1



vector-based representation

$$F_i = (x_{i1}, y_{i1}, x_{i2}, y_{i2}, \dots, x_{in}, y_{in})$$

RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

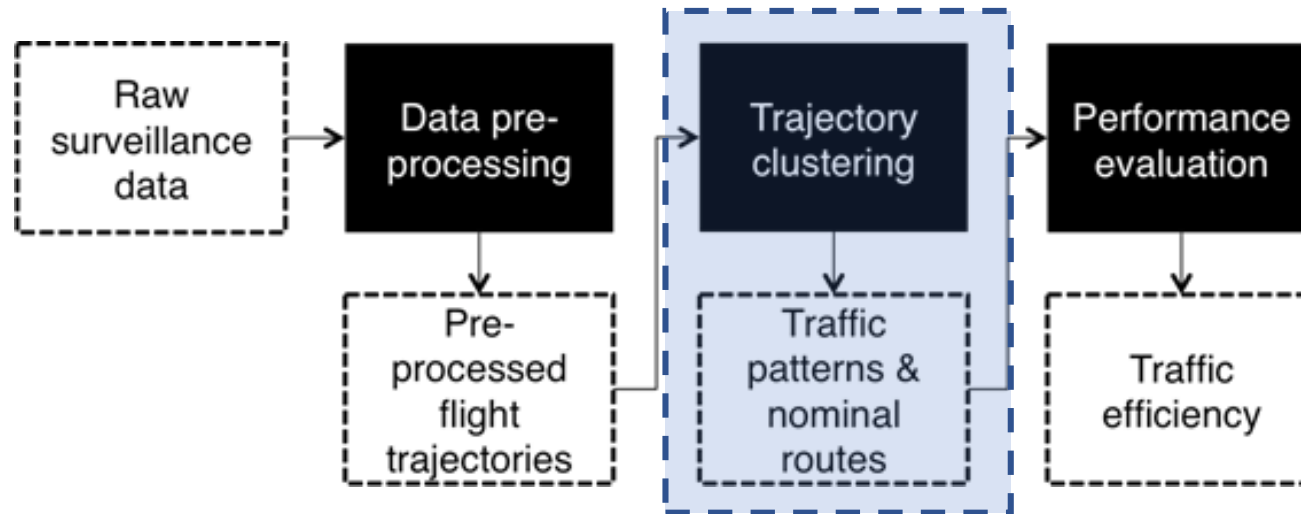
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72975	728	2017-09-12 07:11:34	1505211094	-18.20580	-48.15340	36000.000	354.00000	490.0000	A320	PR-AVP	CGH	BSB	O66170	ONE6170	48A6F
72976	728	2017-09-12 07:12:32	1505211152	-18.07360	-48.16700	36000.000	354.00000	490.0000	A320	PR-AVP	CGH	BSB	O66170	ONE6170	48A6F
72977	728	2017-09-12 07:13:39	1505211219	-17.92320	-48.18240	35400.000	354.00000	491.0000	A320	PR-AVP	CGH	BSB	O66170	ONE6170	48A6F
72978	728	2017-09-12 07:14:37	1505211277	-17.79180	-48.19680	33500.000	350.00000	473.0000	A320	PR-AVP	CGH	BSB	O66170	ONE6170	48A6F
72979	728	2017-09-12 07:15:39	1505211339	-17.66260	-48.23020	31225.000	345.00000	462.0000	A320	PR-AVP	CGH	BSB	O66170	ONE6170	48A6F
72980	728	2017-09-12 07:16:37	1505211397	-17.54260	-48.26180	29200.000	345.00000	447.0000	A320	PR-AVP	CGH	BSB	O66170	ONE6170	48A6F
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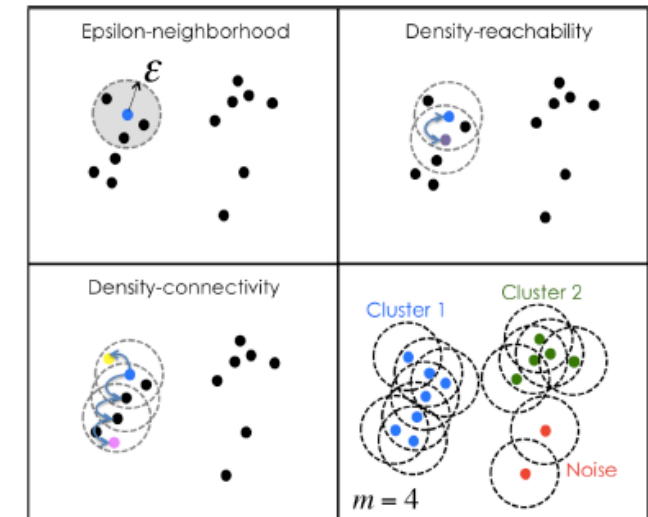
Methodology

Air traffic performance characterization

Step 2



DBSCAN

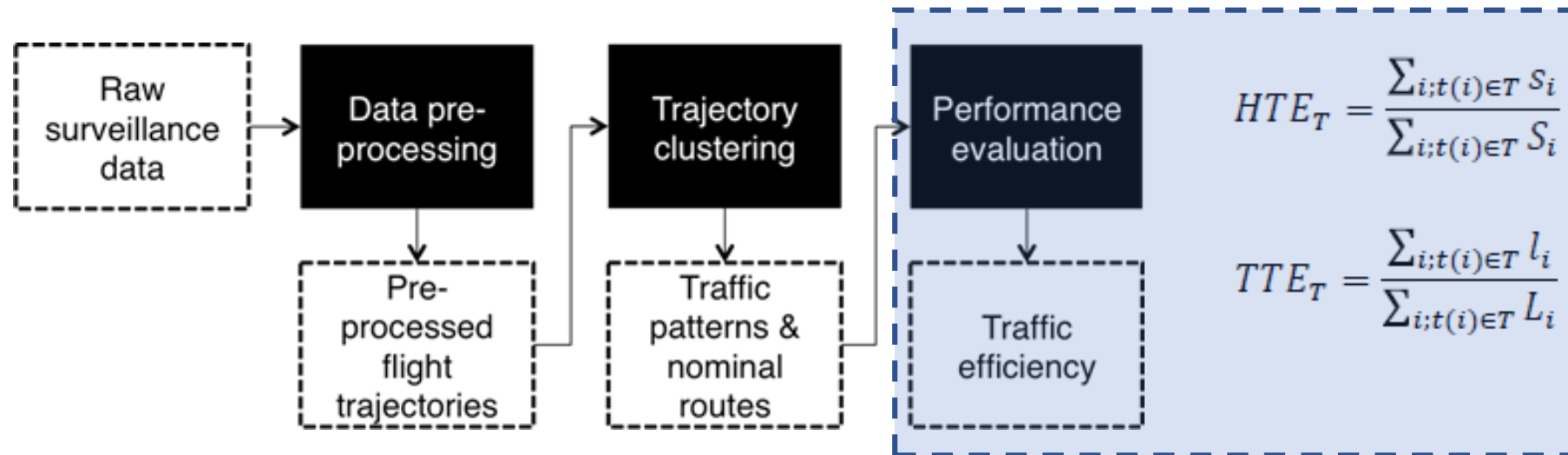


Clustering is an unsupervised learning method that aims at identifying groups of similar observations without prior knowledge

Methodology

Air traffic performance characterization

Step 3



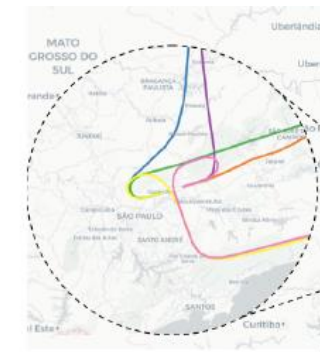
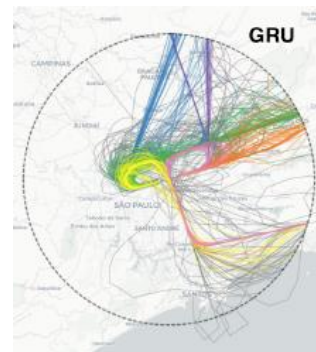
Horizontal and Temporal
Traffic Efficiency

- Performed trajectory
- Cluster centroid

$$HTE_T = \frac{\sum_{i;t(i) \in T} S_i}{\sum_{i;t(i) \in T} S_i}$$

$$TTE_T = \frac{\sum_{i;t(i) \in T} l_i}{\sum_{i;t(i) \in T} L_i}$$

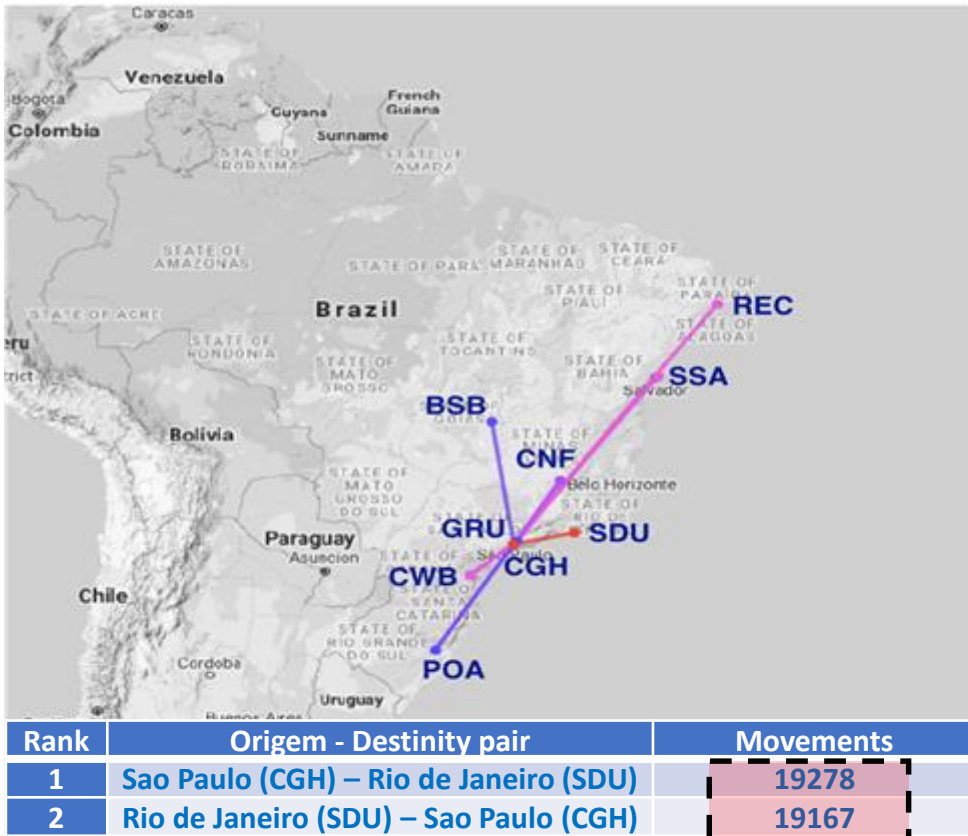
- GANP's indicators
- Other indicators according to the interest of the user



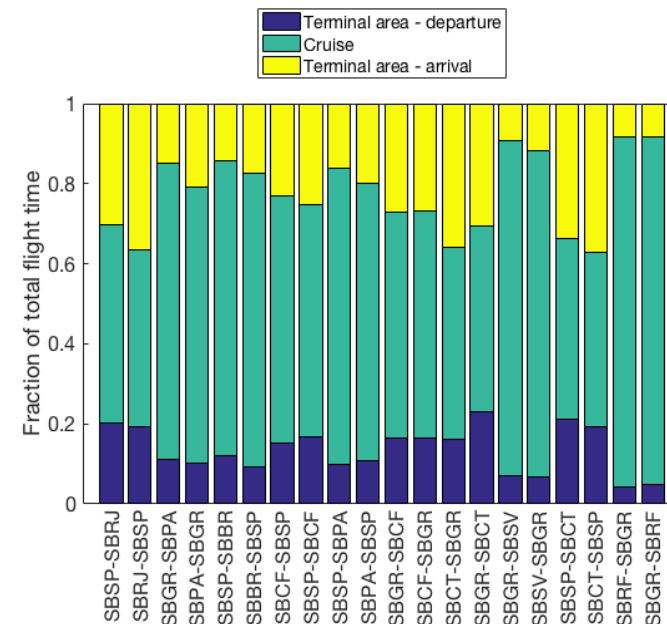
Methodology

Case study

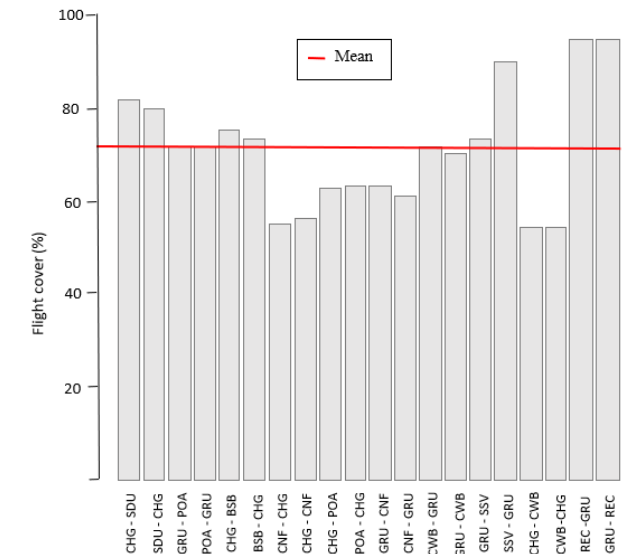
Top-20 OD pairs in Brazil



Flight time by flight phase



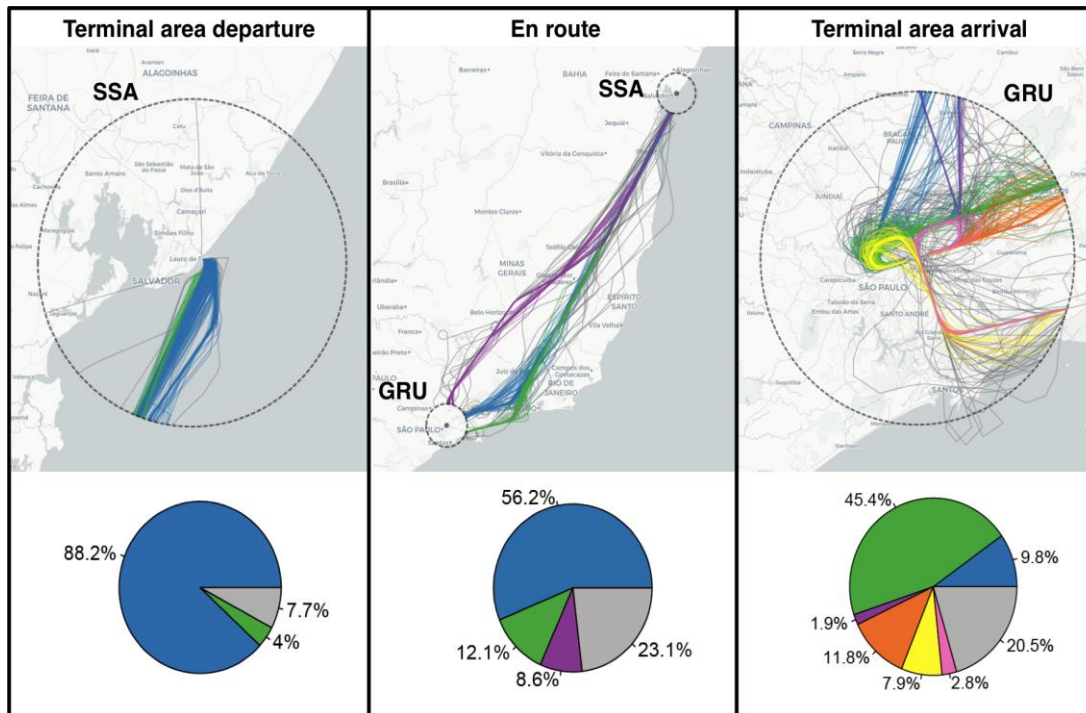
Coverage of flight operations (%)



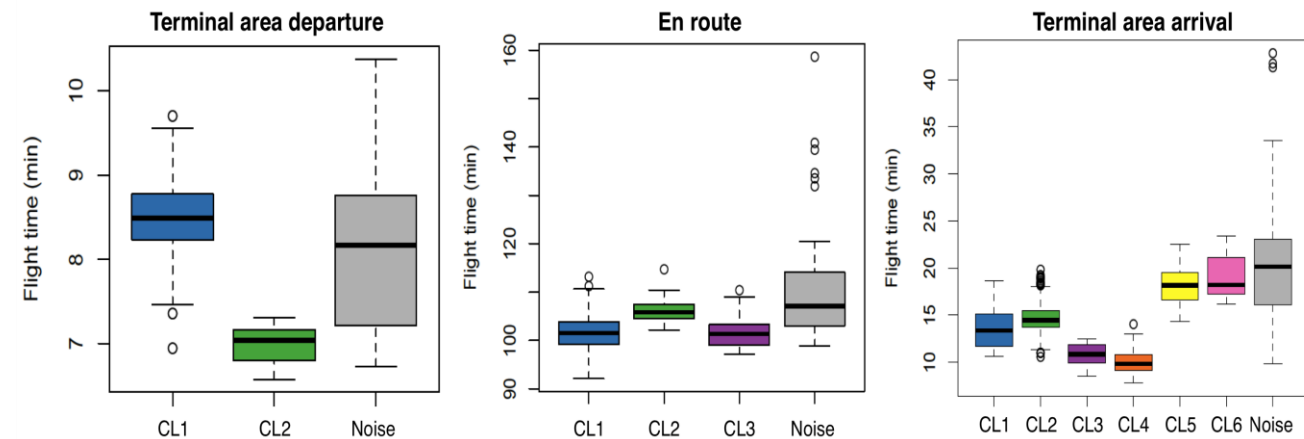
Results and discussion

Identification of air traffic patterns

Clusters of trajectories identified for the SSA-GRU pair



Distribution of flight times for the SSA-GRU pair

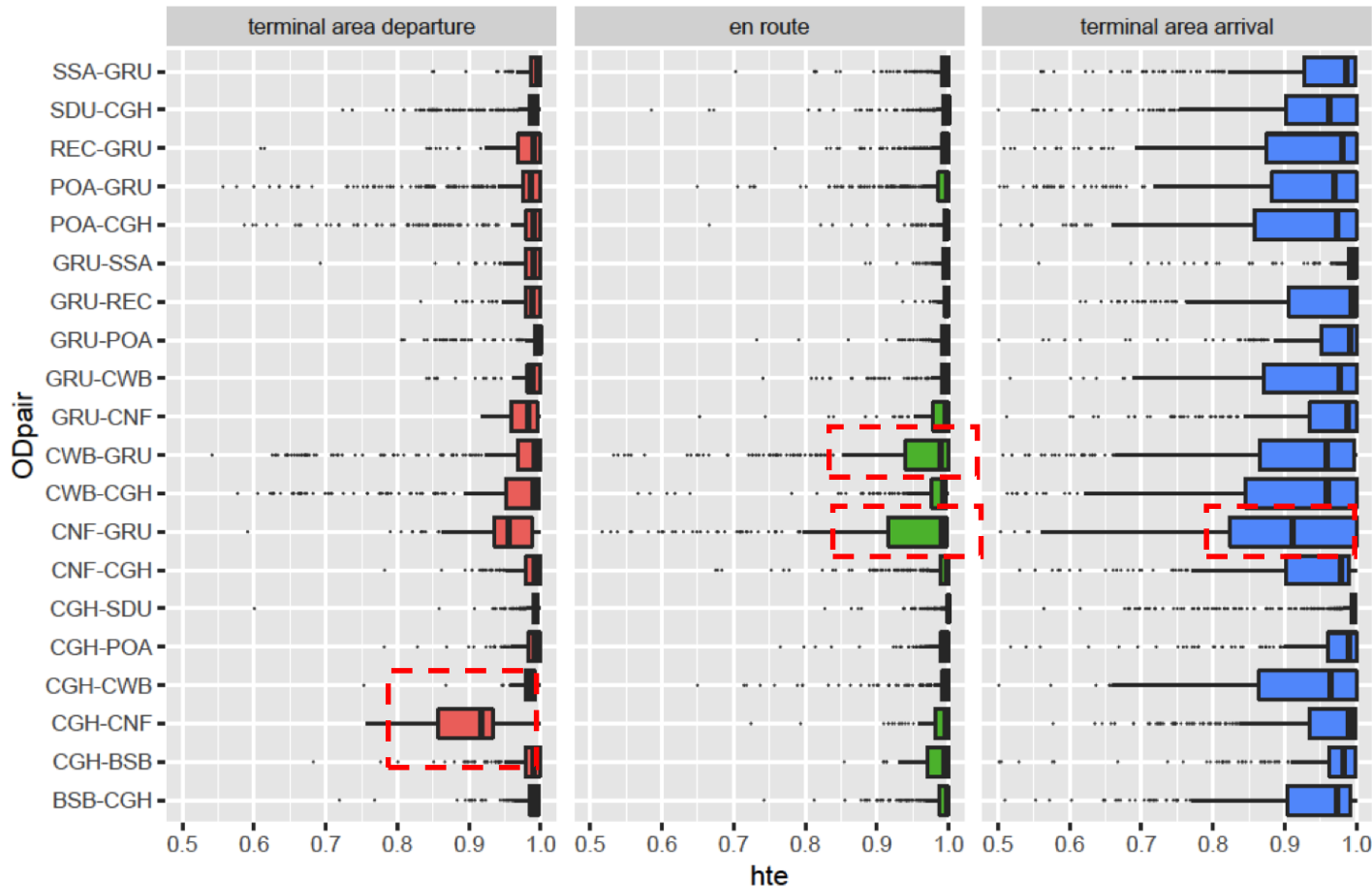


- Number of clusters identified by flight phase
- % of noise

Results and discussion

Assessment of traffic flow efficiency

HTE by flight phase for the top-20 OD pairs in Brazil



HTE 0.0 (Totally inefficient → 1.0 (Full efficient))

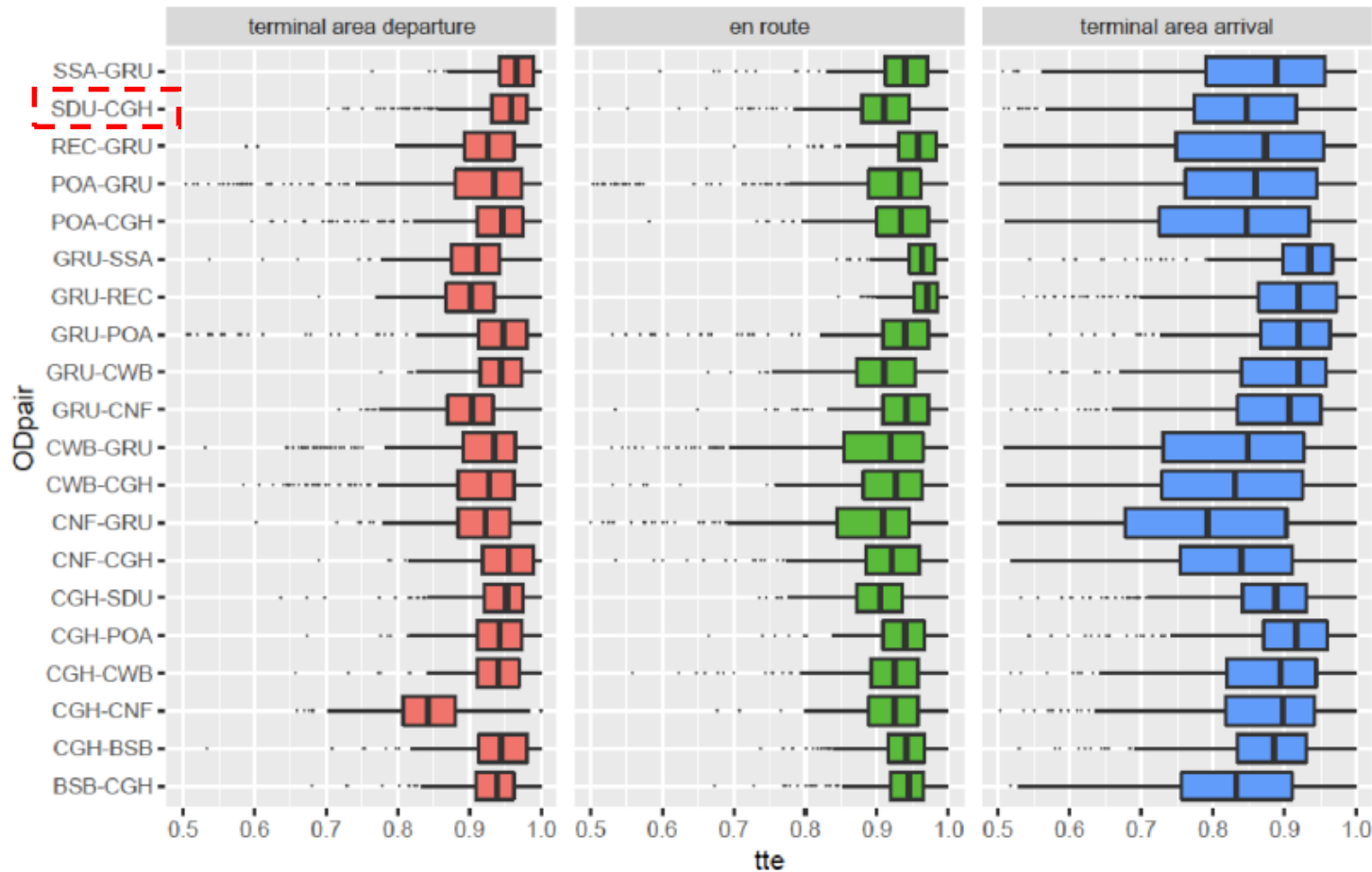
- Terminal area arrival phase - lowest efficiencies on average and highest variability in traffic flow efficiency; trajectories are less predictable; more complex operations
- Some traffic flows stand out



Results and discussion

Assessment of traffic flow efficiency

TTE by flight phase for the top-20 OD pairs in Brazil



- Similar behavior - HTE and TTE tend to be correlated
- SDU-CGH – suggest that delays on this route are more likely to be absorbed with speed control than route changes



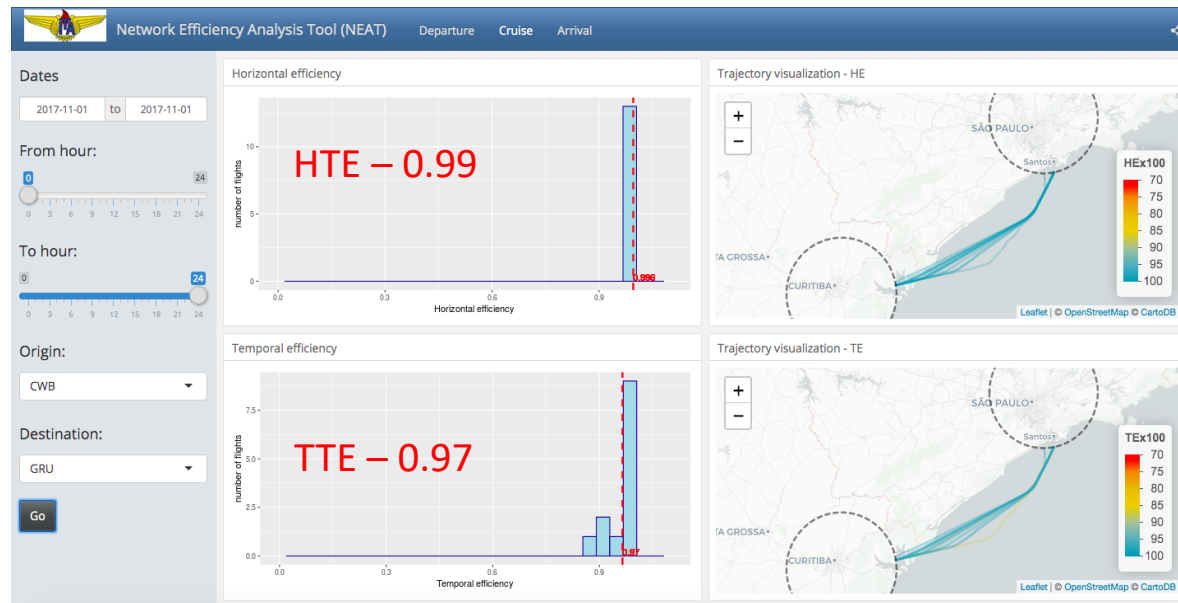
Results and discussion

Network Efficiency Analysis Tool (NEAT)

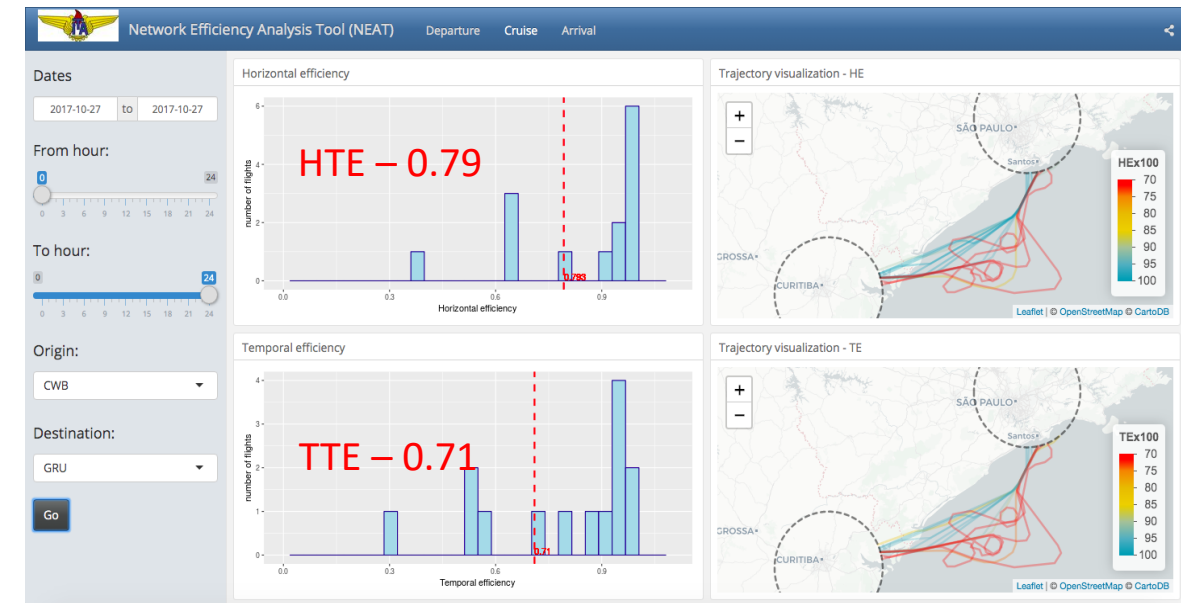
interactive prototype tool for
air traffic performance analysis



Case 1 - clear weather day



Case 2 - day with convective weather impacts

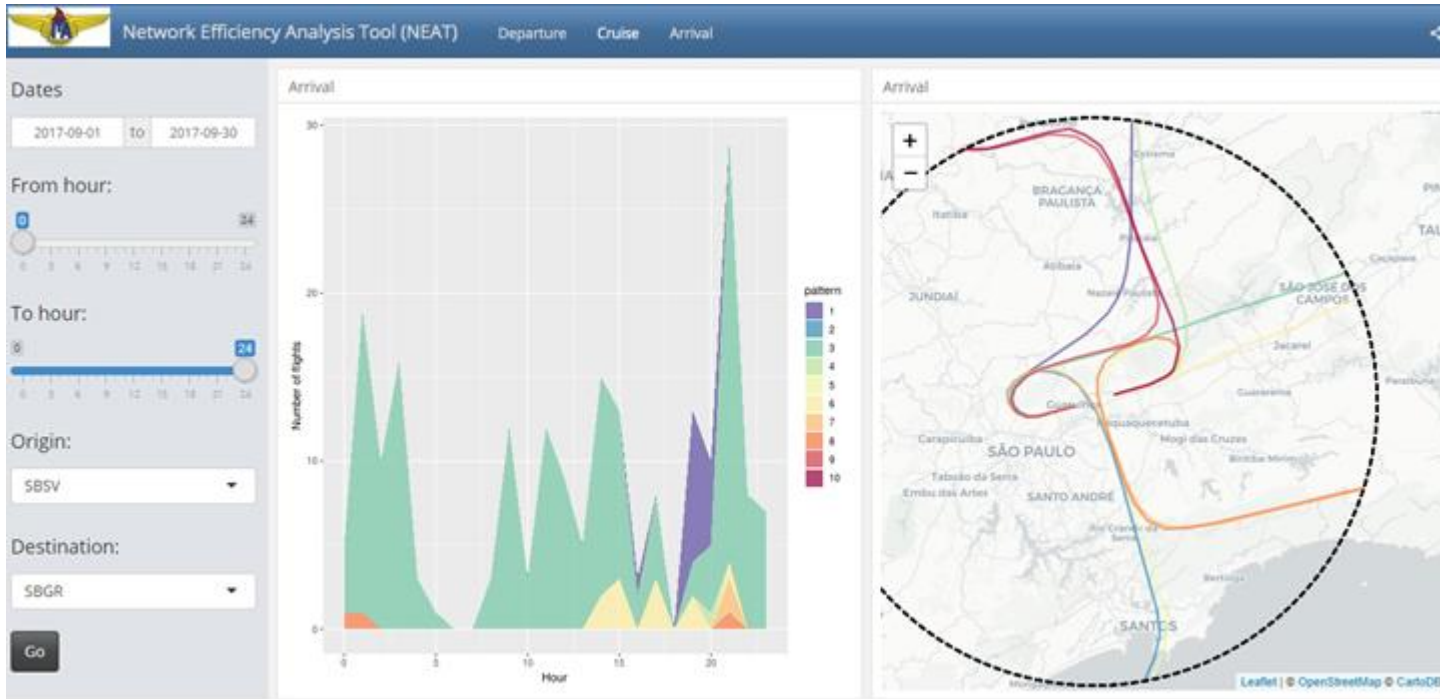


Functionality 1 - Assessment of traffic flow efficiency



Results and discussion

Network Efficiency Analysis Tool (NEAT)



NEAT's
prediction

Airspace design
(complex)

Functionality 2 - Predict the performance of the system



Summary and next steps



Flight trajectory
data analytics

- assessing the air traffic performance
- better understanding how this performance is affected by structural/operational factors
- sources of inefficiencies / new models and tools
- predict and control the performance of the system



prototype tool improvement by including new indicators/features





Thanks a lot!

mcwillianoliveira@gmail.com
mcwillian@ita.br

+55 12 3947 6805

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