Supervised Learning Applied to Air Traffic Trajectory Classification

Christabelle Bosson
Tasos Nikoleris
University Space Research Association - NASA Ames Research Center
Motivation

- New airspace uses and challenges
- Need for autonomy

- Future autonomous Air Traffic Management (ATM) tools will rely on:
  - Aircraft states
  - Machine learning and reasoning
Research Objective

Explore supervised machine learning techniques in the context of aircraft trajectories to predict the landing runway.
Outline

• Background
• Problem Description
• Methodology
• Results
• Conclusion
Background

Hierarchy of Artificial Intelligence

Artificial Intelligence

Machine Learning

Deep Learning
Background

• Applications of Machine Learning in ATM:
  – Air traffic delay prediction
    • Bayesian network [Xu et al., 2005]
    • Decision Trees, Random Forest, and K-Nearest-Neighbors [Choi et al., 2016]
  – Air traffic characterization
    • Clustering [Gariel et al., 2011][Conde Rocha Murça, 2016]
    • Reinforcement learning [Bloem and Bambos, 2015]
  – Air traffic reroute learning
    • Clustering [Arneson, 2015]
    • Data mining [Evans and Lee, 2017]

• Application of Deep Learning in ATM:
  – Flight delay prediction [Kim et al., 2016]
Background

• ATM benefits from Machine Learning

• Improvements of computational resources

• Need for autonomous systems

• Future autonomous ATM tools will rely on the predictions of future aircraft states
Problem Description
Problem Description

• Runway problem formulated as a trajectory classification study
  – Input: time series of aircraft states described by ten features
  – Output: landing runway

• Ten selected features
  – Airline
  – Aircraft weight class
  – TRACON entry location and entry time
  – Time steps of
    • Longitude, latitude, altitude
    • Ground speed, course angle, rate of climb
Methodology

• Data extraction
  – June 2017 DFW arrival flown tracks extracted from the NASA Ames Sherlock Data warehouse
  – 20,822 arrivals in South Flow configuration

• Two datasets are created using one track data point per trajectory, either 3 or 10 min away from landing into DFW
Methodology

Exploration of Machine Learning classification techniques

• Non neural network classifiers
  – Logistic Regression
  – Support Vector Machine
  – Bayes Classifiers
  – K-Nearest-Neighbors
  – Decision Trees
  – Ensemble Methods (bagging and boosting methods)

• Neural network classifiers
  – Multi-Layer Perceptron
  – Convolutional Neural Network
Methodology

- Computation pipeline
  - Preprocessing: data shuffling then K-Fold cross validation
  - Model computation: 21 models
    - 13 non neural network classifiers
    - 8 neural network classifiers
  - Post processing and results analysis

- Implementation: Python, Scikit-Learn and TensorFlow libraries
Results

Three analysis were conducted

• Prediction Analysis
• Sensitivity Analysis
• Feature Importance Analysis
Prediction Analysis

• Objectives:
  – Can the landing runway be accurately predicted with the ten selected features and one track data point per trajectory?
  – How close to the runway must that point be to obtain accurate predictions?

• Results:

<table>
<thead>
<tr>
<th>Trend</th>
<th>Dataset 3min</th>
<th>Dataset 10min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>19.3% to 97.7%</td>
<td>10.9% to 73.2%</td>
</tr>
<tr>
<td>Training times</td>
<td>0.12s to 286.7s</td>
<td>0.12s to 289.9s</td>
</tr>
<tr>
<td>Testing times</td>
<td>0.009s to 2.26s</td>
<td>0.002s to 8.7s</td>
</tr>
</tbody>
</table>
Prediction Analysis

Accuracy

Dataset 3min

Training Time

Dataset 10min

Non Neural Network  Neural Network

Non Neural Network  Neural Network

Best classifier: Gradient Boosting

Worst classifiers: Bayes
Sensitivity Analysis

• Objectives:
  – Can the prediction accuracy obtained with Dataset 10min be improved by training the classifiers using more time steps?
  – What is the sensitivity of each classifier with respect to the amount of time steps used in training?

• Process: start with Dataset 10min, increase the number of time steps to represent each trajectory during training
Sensitivity Analysis

Some classifiers are sensitive to the volume of input data.
Sensitivity Analysis

- The accuracy results are similar using one or more track data points during training.
- The accuracy improvement depends on location not on the number of time steps used during training.

![Gradient Boosting – Accuracy](image)

- **Time series**
- **Single track point**

Accuracy vs. Minutes of Input Data graph:

- Gradient Boosting
- Accuracy

Minutes of Input Data:

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7

Accuracy:

- 0.70
- 0.75
- 0.80
- 0.85
- 0.90
- 0.95
Feature Importance Analysis

• Objectives:
  – What are the most impactful features on the classification results?
  – Does the time step at which the analysis is performed influence the results?

• Process:
  – Gradient Boosting classifier is used
  – 2 cases are considered
    • Case Dataset 3min
    • Case Dataset 10min
Feature Importance Analysis

Note: results depends on the DFW airport geometry
Conclusion

• Exploration of Machine Learning techniques to solve a trajectory-runway classification problem

• Analysis results showed that
  – The different techniques perform differently to solve the problem
  – The closer to the runway the more accurate the landing predictions
  – Neural network models take longer to train than non neural network classifiers
  – Prediction accuracy results are similar whether one or more track data points are used as inputs for training
  – Some classifiers training times are sensitive to the amount of data used as input
  – For DFW, latitude and ground speed dominate 3min away from landing whereas longitude dominates 10min away from landing
Thank you!

Questions?

Christabelle.s.bosson@nasa.gov