

# Spatio-temporal Anomaly Detection, Diagnostics, and Prediction of the Air-traffic Trajectory Deviation using the Convective Weather

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## ABSTRACT

With ahead-of-time aircraft management, we are able to reduce aircraft collision and improve air traffic capacity. However, there are various impact factors which will cause a large deviation between the actual flight and the original flight plan. Such uncertainty will result in an inappropriate decision for flight management. In order to solve this problem, most of the existing research attempt to build up a stochastic trajectory prediction model to capture the influence of the weather. However, the complexity of the weather information and various human factors make it hard to build up an accurate trajectory prediction framework. Our approach considers the problem of trajectory deviation as the "anomaly" and builds up an analytics pipeline for anomaly detection, anomaly diagnostics, and anomaly prediction. For anomaly detection, we propose to apply the CUSUM chart to detect the abnormal trajectory point which differs from the flight plan. For anomaly diagnostics, we would like to link the entire anomalous trajectory sequences with the convective weather data and extract important features based on time-series feature engineering. Furthermore, XGBoost was applied to detect the anomalous trajectory sequences based on the time-series features. For anomaly prediction, we will build up a point-wise prediction framework based on the Hidden Markov Model and Convolutional LSTM to predict the probability that the pilot would deviate from the flight plan. Finally, we demonstrate the significance of the proposed method using real flight data from JFK to LAX.

## 1. INTRODUCTION

In order to improve the safety and efficiency within the National Airspace System (NAS), many researchers develop various models to predict future trajectories based on historical data. With the guidance of those prediction systems, a more efficient flight management system can be achieved, which can provide optimal airspace capacity and resolve the conflicts among different flights. Although prior research on the prediction models has made many progress on the trajectory prediction. The complexity of the problem constrains the prediction accuracy of the model. There are many impact factors such as weather condition, airspace congestion, human factors, and fuel efficiency, which can affect the 4D aircraft trajectories consisting of longitude, latitude, altitude and time. The complex of the problem makes it hard to derive a general model which take all these variables into consideration, especially when most of the variables are not directly measurable.

In this paper, we will tackle the problem by developing the anomaly detection, diagnostics, and prediction framework for the air-traffic trajectory. 1) Anomaly detection: Based on the historical data, we would like to provide a statistical method to detect the actual aircraft trajectories that are significantly deviate from the original flight plan in real time. To achieve this, we will apply the statistical process control method to monitor the deviation in real time. 2) Anomaly diagnostics: We would like to understand the potential factors that could affect the deviation of the air-traffic trajectories. This framework follows the procedure of how a pilot will control the aircraft. If there is strange convective weather along with the flight plan, a pilot will always try to avoid it to ensure the safety of the flight. To achieve this, we will build a machine learning model to find connections between the convective weather and the deviated trajectories and use the feature im-

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portance measure to identify the leading factors. 3) Anomaly prediction: Give the flight plan and weather forecasting data on the flight plan, we would like to predict the probability that the pilot would deviate from the flight plan significantly on each point.

The rest of the paper is organized as follows. Section 2 reviews the related work. Section 3 introduces the data sources and describes the processing procedure for the dataset. Section 4 discusses the details of our data anomaly detection procedure to identify the large deviation of the trajectory and analyze the results. Section 5 discusses the proposed sequence-level anomaly diagnostics procedure for identifying the major root cause of the deviation. Section 6 discusses the proposed point-wise anomaly prediction framework based on Hidden Markov Model and Conv-LSTM. Section 7 summarizes the work and provides a future plan.

## 2. RELATED WORK

There is a vast amount of research focusing on the aircraft trajectories prediction problem. Generally, the prediction strategies can be divided into a stochastic approach and deterministic approach. The deterministic approach usually estimates the future points with physical models such as aerodynamic model, Kalman filter based on kinematic equations (Benavides et al., 2014). However, those approaches are not able to handle the uncertainty of the impact factors. Hence, as the model evolving over time, the prediction accuracy of the system decreasing quickly. On the other hand, to consider the uncertainty of the trajectory, the stochastic approach focus on describing the uncertainty of the prediction results. In the stochastic model, the prediction results usually accompany with a statistical model which is able to make use of the uncertain weather information (Liu and Li, 2015). Qiao et al. (2015) constructed a trajectory prediction model is constructed based on the Hidden Markov Model with a self-adaptive parameter selection algorithm which is able to capture dynamically changing speed. De Leege et al. (2013) presented a generalized linear model which consider various inputs such as aircraft type, weather, and aircraft ground speed. Due to the complexity of trajectory prediction problem, a recurrent neural network framework has been applied which consider the complex impact factors as latent variables (Kim et al., 2017). In this work, it applies a long short-term memory (LSTM) to analyze the temporal behavior and produces the probabilistic information on the future location of the vehicles. Casado et al. (2012) provided a stochastic solution to the problem and addressed the mathematical characterization of the uncertainty sources affecting this model. Kamgarpour et al. (2010) came up with a trajectory generation model by analyzing the current weather information and continuously update the model according to incrementally updated information.

Another line of research focuses on detecting the abnormal trajectories where the abnormal trajectory means a part of a trajectory that is significantly different from others under certain constraint. Under our problem, we can say that the trajectory that follows a flight plan can be considered as normal, otherwise will be denoted as abnormal. Lee et al. (2008) proposed a partition-and-detection framework to find anomalous segments of trajectories from a trajectory data set. Pang et al. (2013) developed the likelihood ratio test to describe traffic patterns which results in accurate and rapid detection of anomalous behavior. However, the above-mentioned research doesn't provide understanding or insights on which portion of the trajectory should be considered anomalous or if abnormal happens, what are the major root causes. In this line of research, some work provides insight into the uncertainty by analyzing possible impact factors.

Inspired those work, we will build up an anomaly detection, diagnostics, and prediction framework for the aircraft trajectories based on the convective weather. Our approach is able to capture multiple weather patterns that influence the flight plan and several important characteristics are extracted through the weather observations.

## 3. DATA DESCRIPTION AND PREPROCESSING

In this section, we will discuss the data description and pre-processing techniques.

For the data, we mainly focus on three datasets. 1) The trajectory dataset records the historical trajectories containing latitude, longitude, altitude and time. 2) The flight plan dataset describes the last filed flight plan which contains several characterized points as guidance to the pilots. 3) The convective weather dataset coming from the Corridor Integrated Weather System(CIWS), which provides convective forecasts information updated every 5 minutes with 5-minute forecast time-steps.

For the trajectory dataset, we only consider the flight from John F. Kennedy International Airport (JFK) to Los Angeles International Airport (LAX) to ignore the influence caused by various routes. During the data pre-processing, we interpolate the trajectories and down-sample the trajectory to 1000 points, which we find it sufficient to describe the trajectory.

## 4. ANOMALY DETECTION

After the above-mentioned data pre-processing techniques, we extract in total 2498 flights from JFK to LAX. In each flight, we collect both the trajectory data and the flight plan data. Based on this information, we propose to build an anomaly detection framework by detecting the deviation of the trajectory data and the flight plan data in real time. We denote  $x_{ik}$  as the coordinate on the  $i^{th}$  flight plan trajectory and  $k^{th}$  point. First, we need to find the corresponding point

$c(x_{ik})$  with the minimum distance. Second, we will compute the distance between these two points as  $d_{x_{ik},c(x_{ik})}$ . Figure 9 illustrates this distance  $d_{x_{ik},c(x_{ik})}$  for  $k = 1, \dots, 1000$  in four flight plans. It can be seen that the actual trajectories actually fluctuate around the flight plan due to the noise, which makes it hard to detect the abnormal sequences only based on the thresholding technique. In conclusion, we need to rely on statistical methods to detect a significant deviation.

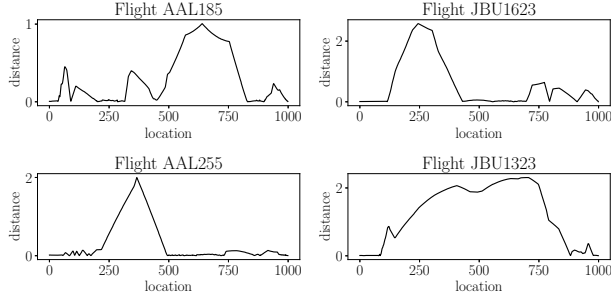


Figure 1. Distance between trajectory and flight plan

In literature, the CUSUM (Pignatiello Jr and Runger, 1990) control chart is proposed for sequential change-point detection under the small mean-shift under the noise. Here, we propose to apply the CUSUM procedure to detect the change point of the deviation of the trajectory. The following equations show how the CUSUM statistics can be calculated according to the flight plan.

$$\begin{aligned}
 S_{0k} &= 0 \\
 S_{n+1,k} &= \max(0, S_{nk} + d_{x_{nk},c(x_{nk})} - \omega_n) \\
 n &= 0, 1, \dots, 999 \\
 k &= 1, \dots, 2498,
 \end{aligned}$$

where  $\omega_n$  is the tuning parameter. Here we set  $\omega_n$  equal to the average of total distance among all flight plan points for all the trajectories so that we can keep the consistency among all the trajectories. We will then set threshold  $T$  for CUSUM result to filter the abnormal sequences. When the cumulative summation  $S_{nk}$  exceeds the threshold, the sequences will be denoted as abnormal. Figure 2 shows the CUSUM result, where we can see that it removes the small changes in the distances.

Finally, we collect all the normal sequences and abnormal sequences for the modeling process. In Figure 3, the red sequences are labeled as abnormal sequences, and we will also define the change point as the start of an abnormal sequence.

For the convective weather dataset, we construct the observation for each trajectory by simply extracting the convective weather on the flight plan points. For the point on the  $k$ th flight plan  $x_{ik}$ , we denote corresponding weather point as  $o_{ik}$ . The weather point will directly describe the weather

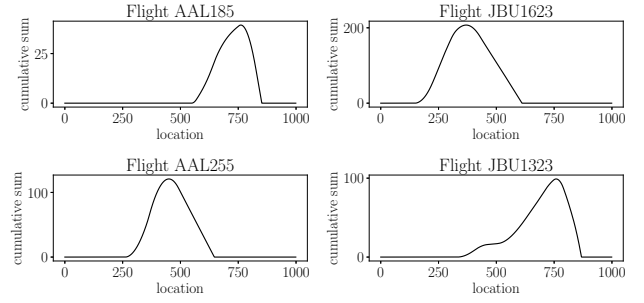


Figure 2. CUSUM result between trajectory and flight plan

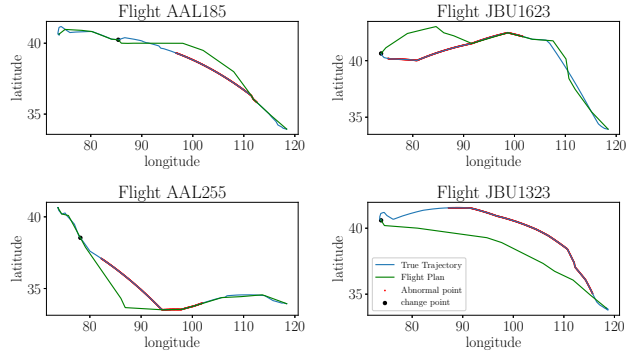


Figure 3. Labeled trajectories

condition on the flight plan. However, in reality, the pilot

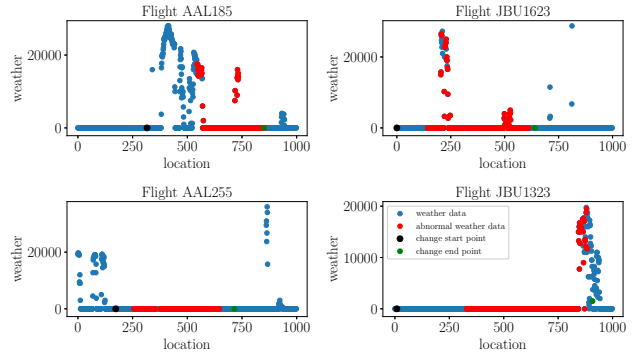


Figure 4. Convective weather visualization

would make the decision based on the neighborhood of the flight trajectory, therefore, at each point of the trajectory, we would extract a  $20 \times 20$  cube of convective weather. Under this situation, we consider a wider range of weather that will influence the trajectory.

After the preprocessing, we end up with 5082 weather sequences labeled as normal sequences or abnormal sequences. Here we will use  $o_{ij}$  to denote the weather at  $i^{th}$  position on  $j^{th}$  sequence. Figure 4 shows the magnitude of the convective

weather along the flight trajectory. The red points denote the position that deviates from the trajectory plan. From the top two figures, we can see that the pilot decides to deviate from the flight plan as soon as the significant convective weather is noticed. In the bottom left figure, we can see that some times aircraft deviates even though there is no influence caused by weather. In the bottom right figure, the pilot starts to deviate even though the convective weather is still far away. Hence, it is hard to recognize a consistent weather pattern that will influence the pilot's decision. In the next section, we will discuss two models to discover such relationships. Figure 5 detailed the complete data processing procedure.

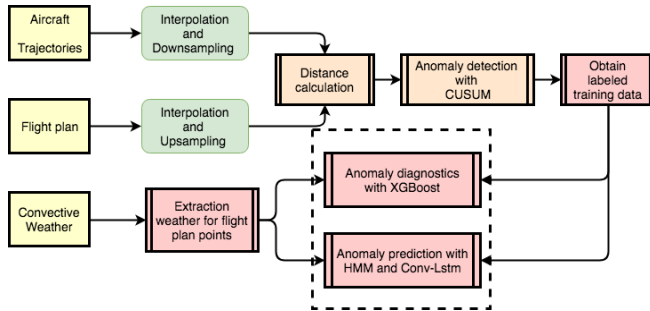


Figure 5. Data preparation

## 5. SEQUENCE-LEVEL ANOMALY DIAGNOSTICS

In this section, we will introduce two major frameworks to detect the abnormal sequences based on the convective weather. The first is to build a machine learning classifier to classify the entire sequence, which we developed based on combining XGBoost and time-series feature engineering.

XGBoost(Chen and Guestrin, 2016) is one of the most popular supervised machine learning technique which applies the gradient boosting decision tree algorithm. Due to its efficiency and high accuracy on the supervised learning problems, we would like to apply this method to our problems.

### 5.1. Feature Engineering

Before we set up the XGBoost framework, we first extract potentially important features through the weather sequences. In order to use the time series of the convective weather as the predictors, we first need to perform feature engineering method to extract useful features, such as the maximum, minimum, longest sequence above the mean, Fourier coefficient, etc. To achieve this, we apply a python package called *tsfresh* (Christ et al., 2018), which automatically calculates 782 common time series features. More specifically, we filter out short weather sequences, which end up with 5082 weather sequences. Then, we train the XGBoost model with 80% selected sequences and test the prediction accuracy with the rest of the sequences. Finally, we will present the features with

the highest SHAP values(Lundberg and Lee, 2017) and explain the contribution of the features.

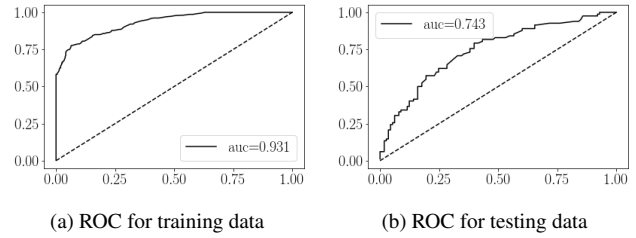


Figure 6. ROC results

## 5.2. Results

With the XGBoost method, we are able to first give the probability of entire sequences being anomaly given the weather information. Here, we will present the result of our model and talk about several important features selected through the model based on SHAP values.

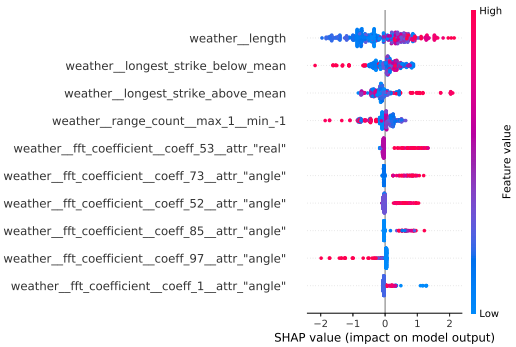


Figure 7. Distribution of shap values among all samples

With the above setting, we got 0.931 average training AUC and 0.743 average testing AUC. Since the AUC is above 0.5, which shows indeed the convective weather is quite a significant factor for the aviation trajectory deviation. Beyond the prediction accuracy, we would also like to understand what convective weather pattern/feature is the major root cause. Here we present ten features with the highest contribution to the prediction accuracy. From Fig.8, we are able to explain the features with highest SHAP values according to the corresponding physical meanings. *weather\_length* shows the length of the abnormal weather sequence. Longer abnormal weather sequences will have a higher probability causing a deviation. *weather\_longest\_strike\_below\_mean* shows the length of the longest consecutive subsequence in each weather sequence that is smaller than the mean of the magnitude of weather sequence. Similarly, *weather\_longest\_strike\_above\_mean*, shows the subsequence that has the severe convective weather. Those two

features capture the abnormal phenomenon along a weather sequence which provide a good guidance to understand how a pilot make the decision.

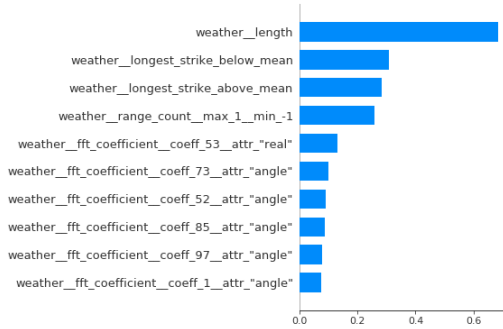


Figure 8. Average impact on model output magnitude

## 6. POINT-WISE ANOMALY PREDICTION

Anomaly Diagnostics technique presented in Section 5 is useful to identify the major root cause when a trajectory deviation is identified. In many applications, it would also be beneficial if we can actually predict whether the pilot would deviate from the flight plan given the weather forecasting data. In this section, we will present a point-wise anomaly prediction method on the flight plan to decide the pilot would deviate from the flight plan according to the weather information. In the modeling approach, we will mainly compare Hidden Markov Model and Convolutional LSTM for point-wise anomaly prediction accuracy.

### 6.1. Hidden Markov Model

Hidden Markov Model is known as an unsupervised learning technique which can recognize the underlying state of a system based on observations. Here we assume that the system is moving between two states which are the normal state and abnormal state. The convective weather is the realization of those hidden states. We are trying to find the most likely state sequence along with a flight plan based on the convective weather. Unlike supervised learning technique, it is not necessary to label the data ahead of modeling. We can directly fit the trajectory and the model will classify all the points directly.

#### 6.1.1. Implementation

Under our problem, we have two hidden states which will be predicted through the Viterbi algorithm. We select 80% sequences as training data to fit the model parameters with the EM algorithm and compute the prediction accuracy with the rest of the data. The observations for the HMM model will be the convective weather which is continuous. There will be 1000 states in each sequence which corresponds to

the weather information at that position. Under our problem, we have two hidden states which will be predicted through the Viterbi algorithm. We select 80% sequences as training data to fit the model parameters with the EM algorithm and compute the prediction accuracy with the rest of the data. The observations for the HMM model will be the convective weather which is continuous. There will be 1000 states in each sequence which corresponds to the weather information at that position. Here I will define the parameters for our Hidden Markov Model as following.

- Let  $\mathbf{S} = \{S_1, S_2\}$  denote two hidden states where  $S_1$  denotes the abnormal condition and  $S_2$  denotes the normal condition.
- A transition probability matrix is a two by two matrix which can be defined as  $\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$ ,  $a_{ij}$  is the probability of an aircraft changing between normal and abnormal state.
- Emission probabilities  $\mathbf{B} = \{b_i(o)\}, i \in \{1, 2\}$  is the probability of continuous convective weather being observed at state  $S_i$ .
- Initial probabilities  $\pi = \{\pi_1, \pi_2\}$  denotes the probability if a trajectory deviates as soon as it takes off.

Through the learning step, we will find a set of above parameters that will maximize the likelihood of the occurrence of the observations. And we want to find the sequence of states  $s = \{s_1, s_2, \dots, s_{1000}\}$  that provides the best result for the observation sequences  $O = \{o_1, o_2, \dots, o_{1000}\}$

### 6.1.2. Results

Comparing to the supervised learning, we are able to get more information through this process. We are able to get the probability for all the points along a sequence. Figure 9 shows the prediction result for the previous four trajectories. And the black points are predicted as abnormal sequences according to the convective weather. We can see that HMM is able to handle small variations between normal and abnormal state from the figures in the first row. However, for large deviation as shown in the bottom right figure, it is hard for HMM to capture the whole sequence. From Figure.4, we know that severe convective weather for JBU1323 only happens at the end of the route. But the pilot decides to deviate from the flight at the start of the route which shows that it is not enough to predict the trajectory simply with weather information. Some other information like human factors, traffic load, fuel efficiency will all impact the actual trajectory. Thus, the model with convective weather can only provide guidance to the pilot and air traffic management system. From Figure 9, we can also realize that there are multiple different decisions made by a pilot given the same weather condition. However, some of the actions are normal and others are not. Thus, through

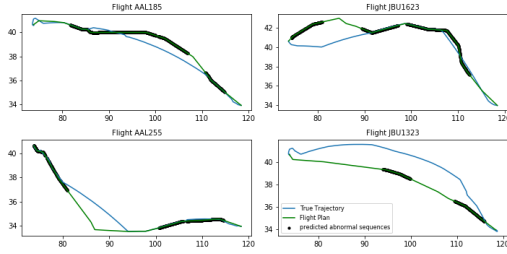


Figure 9. Prediction results from Hidden Markov Model

the Hidden Markov Model, we can also acquire information about if an action is normal or not. Furthermore, such information reflects that if a trajectory is predictable or not. Comparing Figure 9 with Figure 4, we can see that Flight AAL 185 and JBU 1623 follow the normal pattern i.e. the aircraft will deviate from the flight plan when there is bad convective weather. However, flight AAL 255 is an example of the trajectory that is not predictable where the pilot starts to deviate when there is no severe convective weather around. Based on those understanding, we build up a framework to detect abnormal behavior through HMM.

## 6.2. Conv-LSTM Model

In this subsection, we will build a convolutional LSTM architecture to handle the complex spatio-temporal dependencies in the convective weather.

### 6.2.1. Model Architecture

Neural Network has achieved great success in various machine learning tasks due to the increasing computational power and the ability to model the data with the complex spatial and temporal relationship. In this section, we proposed a Conv-LSTM architecture with Convolutional Neural Network (CNN) and Long short term memory (LSTM). More specifically, we first prepare our data as a 4D tensor of size  $n_{sample} \times n_T \times n_x \times n_y$  to  $2500 \times 999 \times 50$ .  $n_{sample} = 2500$  is the number of flight sequences that we observed. For each flight sequence, we extract  $n_T = 999$  time points. For each time, we will use the  $n_x \times n_y$  convective weather cube, where  $n_x = n_y = 20$ . We choose  $n_x = n_y = 20$  since this is the radius that the aircraft would normally react to. After the data preparation, we first apply a CNN framework to extract high-level spatial features from the  $n_x \times n_y$  weather cube. Then the extracted features are used to build bi-directional LSTM model to classify the point-wise project deviation. We will use binary classification, with label 1 representing the deviation of the flight. The label is obtained from the anomaly detection procedure in Section 4. Figure 10 shows the detailed architecture of our model. For the CNN layers, we include a convolutional layer, rectified linear unit (ReLU) and a pooling layer. The convolutional layer is able to extract important features and learn the useful filters of the input weather

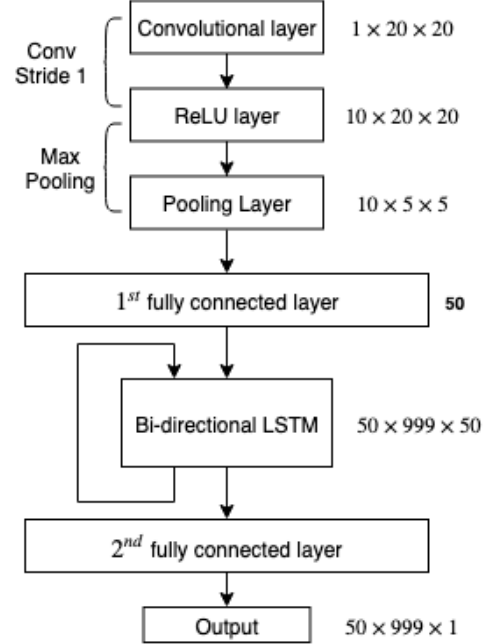


Figure 10. Conv-LSTM architecture

cube. ReLU is used for the nonlinear transformation of these features. Max-pooling is used to reduce the output spatial dimension. Finally, these extracted low-dimensional features are linked together via a bi-directional LSTM to extract the temporal features from the trajectories. Bi-directional LSTM is able to capture the information not only from the past but also from the future, which is important in our problem, since a pilot will decide to deviate from the original flight plan if the weather condition in the future is bad (Graves and Schmidhuber, 2005). Finally, we add a fully connected layer with ReLU and Sigmoid function to classify each trajectory point as normal or abnormal with binary cross-entropy loss function

### 6.3. Comparing HMM and Conv-LSTM for Anomaly Prediction

From Figure 11, we can compare the results from HMM and Conv-LSTM in terms of AUC performance. Here we compute the AUC score based on the point-wise classification accuracy. First of all, both models can provide AUC larger than 0.5, showing some prediction power. It worth noting that the AUC score is different from the AUC score presented in Section 5, which the entire sequence is being classified as normal or abnormal. Since the point-wise trajectory prediction problem is much more challenging than the sequence-level anomaly classification problem, the AUC obtained from the HMM and Conv-LSTM is lower. More specifically, Conv-LSTM provides the AUC score around 0.61, which is much higher than the AUC by HMM, which is around 0.527. The reason for the bad performance of HMM is due to the number of state in HMM is very limited, which is insufficient to

propagate the complex spatio-temporal dynamics. Furthermore, HMM assumes the linear transition matrix, which is over-simplified compared to the proposed Conv-LSTM approach.

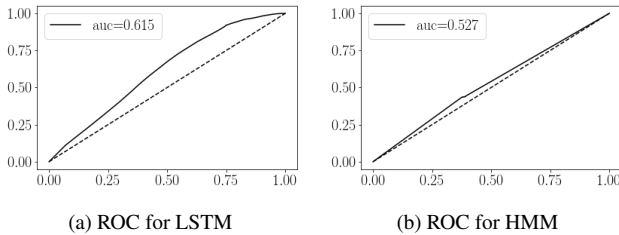


Figure 11. ROC results comparison

## 7. CONCLUSION

The paper proposes an anomaly detection, diagnostics, and prediction procedure for the air traffic management system. We concentrate on the impact of convective weather on the flight plan and build up a pipeline to process the dataset. The distance between flight plan and actual trajectories is fed to the CUSUM procedure to detect the abnormal sequences. To understand how the deviation of trajectory happens, we apply the predictive modeling, named the XGBoost, to link the abnormal weather sequence with the time-series features extracted from the convective weather. In this work, we are able to achieve great prediction power to classify the anomaly sequence. Furthermore, the feature importance score is proposed to identify the most impactful features from the convective weather that affect the trajectory, such as the quantile, Fourier coefficient and wavelet coefficient. Finally, we propose an anomaly prediction framework based on HMM and ConvLSTM. In general, the AUC score shows that ConvLSTM performs better than HMM, this is partially due to the power of Conv-LSTM on learning complex spatio-temporal features directly from the 4D weather cube data. For our future study, we will make use of other information than the convective weather for a better diagnostics and prediction accuracy.

## REFERENCES

- Jose V Benavides, John Kaneshige, Shivanjli Sharma, Ramesh Panda, and Mieczyslaw Steglinski. Implementation of a trajectory prediction function for trajectory based operations. In *AIAA Atmospheric Flight Mechanics Conference*, page 2198, 2014.
- Enrique Casado, Colin Goodchild, and Miguel Vilaplana. Identification and initial characterization of sources of uncertainty affecting the performance of future trajectory management automation systems. In *Proceedings of the 2nd International Conference on Application and Theory of Automation in Command and Control Systems*, pages 170–175. IRIT Press, 2012.
- Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794. ACM, 2016.
- Maximilian Christ, Nils Braun, Julius Neuffer, and Andreas W Kempa-Liehr. Time series feature extraction on basis of scalable hypothesis tests (tsfresh—a python package). *Neurocomputing*, 307:72–77, 2018.
- Arjen De Leege, Marinus van Paassen, and Max Mulder. A machine learning approach to trajectory prediction. In *AIAA Guidance, Navigation, and Control (GNC) Conference*, page 4782, 2013.
- Alex Graves and Jürgen Schmidhuber. Framewise phoneme classification with bidirectional lstm and other neural network architectures. *Neural Networks*, 18(5-6):602–610, 2005.
- Maryam Kamgarpour, Vera Dadok, and Claire Tomlin. Trajectory generation for aircraft subject to dynamic weather uncertainty. In *49th IEEE Conference on Decision and Control (CDC)*, pages 2063–2068. IEEE, 2010.
- ByeoungDo Kim, Chang Mook Kang, Jaekyum Kim, Seung Hi Lee, Chung Choo Chung, and Jun Won Choi. Probabilistic vehicle trajectory prediction over occupancy grid map via recurrent neural network. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, pages 399–404. IEEE, 2017.
- Jaе-Gil Lee, Jiawei Han, and Xiaolei Li. Trajectory outlier detection: A partition-and-detect framework. In *2008 IEEE 24th International Conference on Data Engineering*, pages 140–149. IEEE, 2008.
- Yu Liu and X Rong Li. Intent based trajectory prediction by multiple model prediction and smoothing. In *AIAA Guidance, Navigation, and Control Conference*, page 1324, 2015.
- Scott M Lundberg and Su-In Lee. A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems*, pages 4765–4774, 2017.
- Linsey Xiaolin Pang, Sanjay Chawla, Wei Liu, and Yu Zheng. On detection of emerging anomalous traffic patterns using gps data. *Data & Knowledge Engineering*, 87:357–373, 2013.
- Joseph J Pignatiello Jr and George C Runger. Comparisons of multivariate cusum charts. *Journal of quality technology*, 22(3):173–186, 1990.
- Shaojie Qiao, Dayong Shen, Xiaoteng Wang, Nan Han, and William Zhu. A self-adaptive parameter selection trajectory prediction approach via hidden markov models. *IEEE Transactions on Intelligent Transportation Systems*, 16(1): 284–296, 2015.

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