Explaining Aviation Safety Incidents Using Deep Learned Precursors

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ABSTRACT

Although aviation accidents are rare, safety incidents occur more frequently and require careful analysis for providing actionable recommendations to improve safety. Automatically analyzing safety incidents using flight data is challenging because of the absence of labels on timestep-wise events in a flight, complexity of multidimensional data, and lack of scalable tools to perform analysis over large number of events. In this work, we propose a precursor mining algorithm that identifies correlated patterns in multidimensional time series to explain an adverse event. Precursors are valuable to systems health and safety monitoring in explaining and forecasting anomalies. Current precursor mining methods suffer from poor scalability to high dimensional time series data and in capturing long-term memory. We propose an approach by combining multiple-instance learning (MIL) and deep recurrent neural networks (DRNN) to take advantage of MIL’s ability to model weakly-supervised data and DRNN’s ability to model long term memory processes, to scale well to high dimensional data and to large volumes of data using GPU parallelism. We apply the proposed method to find precursors and offer explanations to high speed exceedance safety incidents using commercial flight data.

KEYWORDS

Precursor, Deep Learning, Multiple-Instance Learning, Anomaly Detection, Prognostics, Aviation

1 INTRODUCTION

Explanations for Aviation safety incidents may be required for many reasons. A safety analyst working for a commercial airlines company may be interested in finding root causes of these incidents to improve the fleet’s safety, to do predictive maintenance, to monitor human factors such as fatigue, and situational awareness to improve pilot training etc. On the other hand, FAA and NASA who are directly monitoring airspace safety often require such explanations to inform better airspace designs, improve policies, regulations and standard operating procedures. Finally, event explanations may accelerate investigations about past safety incidents and accidents that are conducted by organizations such as the National Transportation Safety Board (NTSB).

Currently, safety incidents are explained manually; a group of human experts analyze a given safety incident and offer explanations using causal factors and correlated events that occurred in the flight. However, this is not a scalable approach with the numerous safety incidents that occur and with the growth in the volume of sensory data. The data recorded from short to medium range flights of a commercial passenger airline flying a narrow-body jet aircraft includes on average about 900 exceedance incidents per day out of about 1000 flights that were operated\(^1\). It becomes impossible to manually analyze these events on a case-by-case basis to come up with actionable information to improve safety in a timely manner. This paper presents an automated way of using data mining to identify key correlated events in the data to explain a safety incident.

We propose using precursors as a means to identify key events in the flight time series data. A precursor is any correlated event that occurs prior to the safety incident with a high likelihood of the safety incident occurring in the future. Precursors give insights into the root causes of the failure and provide actionable insights with early alerts and corrective actions. To provide useful explanations, precursor mining aims to answer the following questions - "When do degraded states begin to appear?" "What are the degraded states?" "Are there corrective actions?" "What is the likelihood that the safety incident will occur?". For example, our method identified precursors to a particular high speed exceedance (safety incident) that was used to explain the incident as follows. During the landing phase of the flight (see Figure 1), about 25 miles away from the runway, most variables were normal indicating a "safe state." Correspondingly the probability of the safety incident was close to zero. At about 2500 ft altitude and 13 miles away, the flight made its turn to align with the runway when the speed reference was set incorrectly (unusually high) which caused the engine speed and consequently the flight’s speed to be high. Correspondingly the probability of the safety incident also increased. At about 8 miles out, the speed reference was corrected (reduced) which caused the airspeed to drop. This is indicated by a decreasing probability of failure indicating possible corrective actions. However, from about 1500 ft altitude, the likelihood increases because the flaps were delayed. Flaps are friction surfaces that help reduce airspeed. In this case, flaps are not set on time which caused the airspeed to remain high. This happened so close to the checkpoint that the safety incident was flagged. Thus, a 50 dimensional time series data from a flight was summarized to provide explanations about key events that occurred before the safety incident.

Precursor mining is a weakly-supervised learning problem. Usually we have easy access to a label that indicates the safety incident in a flight. The labels may come from aviation safety reporting system (ASRS) [25] where the flight crew volunteer to report safety incidents during their flight, or from exceedence reports that are automatically generated by using domain based rules to identify safety incidents. While a flight-level label is available, the labels for precursors within a flight are usually not available, which makes the explanation task challenging. To address this, our past work

\(^1\)The exceedances considered here fall under severity 2 and 3 while severity 1 is often ignored because of its mildness. Also note not all exceedences have equal safety concern.
focused on using the flight-level information as a weak supervision to obtain the underlying decision making behavior using inverse reinforcement learning [16]. In this paper, we propose to use another weakly supervised learning approach called Multiple-Instance Learning (MIL) to use the flight-level label to infer timestep wise event labels.

A MIL setting typically assumes a set of data instances grouped in the form of bags. The bag level labels are known while the instance labels are unknown. The task of MIL is to learn a model to either predict the bag labels or instance labels or both. An assumption is usually made in MIL that relates the instance-level labels to the bag-level labels. A standard assumption of MIL states that the bag is labeled positive if there is at least one positive instance in the bag while it is labeled negative if all instances in the bag are negative. A more detailed discussion on MIL and the assumptions involved can be found in [4, 11, 12]. The standard MIL formulation does not consider time connection between instances and its performance drops when applied to time series data [13] such as the flight data considered in this work. To address this, we propose a deep temporal multiple-instance learning (DT-MIL) that extends the MIL framework to be applied to time series data. Further, by having deep neural network models, the approach can be scaled better for large data sets using GPU parallelism. The main contributions of the paper include

(1) a novel deep temporal multiple-instance learning (DT-MIL) framework that combines multiple-instance learning with deep recurrent neural networks suitable for weakly-supervised learning problems involving time series or sequential data.

(2) a novel way to explain safety incidents using automatically mined precursors from data.

(3) detailed experiments, analysis and precursor insights using real-world aviation data.

The rest of the paper is organized as follows. We discuss related work in Section 2. In Section 3, the precursor mining problem is formulated with an intuition about our approach followed by description of our DT-MIL model. The discussion about data, the considered safety incident and experiments are in Section 4. In Section 5, we present quantitative results of the DT-MIL method and discuss the explanations offered for a few representative flights. We then summarize the work and conclude in Section 6.

2 LITERATURE REVIEW

The application of data mining and machine learning methods for aviation safety is not new. NASA Ames Research Center has been pioneering this line of work for several years and has developed methods such as Orca [6], i-Orca [7], Inductive Monitoring System [15], Multiple Kernel Anomaly Detection (MKAD) [9], ELM based anomaly detection [18], among others. For event detection and optimal alarm systems, NASA has open-sourced the Adverse Condition and Critical Event Prediction Toolbox (ACCEPT) which is a suite of machine learning algorithms [22]. Outside of NASA, much of the work revolves around finding anomalies in flight data [21, 26] or in text reports [3, 28]. Another related research is in understanding human factors in flight safety [20]. The above work aims at detecting unsafe patterns but offers little or no automated explanations.

Recently, several approaches for precursor mining have been proposed. The Automatic Discovery of Precursors in Time Series 16

Figure 1: Explanations in the form of key events identified by precursor mining algorithm for a flight that had a high speed exceedance (safety incident). Important events are shown by blue arrows, precursors are marked with red circles while a green star is used to indicate the safety incident.
(ADOPT) finds precursors using multidimensional sensory time series data and has been applied to single flight incidents such as a take-off stall risk [17], as well as to incidents such as go-around [16] that involve interactions between multiple flights. Another approach is using a nested multiple-instance learning that finds precursors to protests and social events using text data [23]. Other story telling based algorithms exist, for instance [14], that are aimed at entity networks and using text documents but it is not trivial to see its applicability for multidimensional sensory data. Compared to the above methods, our approach combines multiple-instance learning (MIL) and deep recurrent neural networks (DRNN) to take advantage of MIL’s ability to model weakly-supervised data and DRNN’s ability to model long term memory processes, to scale well to high dimensional data and to large volumes of data using GPU parallelism.

Multiple-instance learning was first proposed by Dietterich et al. [11] which was then extended using support vector machines [4] and neural networks [24]. There exists some work on using multiple instance learning for temporal data such as using autoregressive hidden Markov models [13], and using recurrent neural networks [10] mainly to learn a prototype vector using the instances which is then used in the recurrent network for supervised classification of the bags. The motivation of this paper appears to be different from ours and it does not take advantage of the superior capabilities of long-term memory units such as the LSTM units. Only recently, deep multiple-instance learning has been proposed and used in the context of object detection and annotations [5, 27, 29]. Our work is an extension to the prior literature by combining multiple-instance learning with deep recurrent neural networks.

3 METHODOLOGY

In this section, we add more formalism to the precursor mining problem extending our earlier work [16], discuss the idea behind using multiple-instance learning and introduce the deep temporal multiple-instance learning (DT-MIL) framework for this problem.

3.1 Precursor Mining Problem

The problem of precursor mining can be stated as follows. Let the time series data be represented by \( X \) with dimensions \((N, L, d)\), where \( N \) denotes the number of time series records, \( L \) the maximum length of time series and \( d \) the number of sensory variables. Let an instance in record \( i \) at time \( t \) be given by

\[
e_i^t = f(x_1^i, x_2^i, ..., x_d^i),
\]

where \( f(.) \) is some function that captures a compressed representation of the sequence \( x_1^i, x_2^i, ..., x_d^i \). Given the data \( x_j^i \) and the corresponding safety incident label \( Y_j^i \), the goal of precursor mining is to find a set of time instances \( \{j\}, 1 \leq j \leq L \) for which

\[
P(\text{safety incident}|e_j^i) > \delta .
\]

Note that the labels are binary; i.e., \( Y_j^i = 1 \) implies a safety incident reported in \( X_j^i \). The label is also for the entire flight \( X_j^i \) which is a collection of instances \( e_1^i, e_2^i, ..., e_d^i \). Each \( x_j^i \) is a vector of \( d \) sensory variables such as airspeed, altitude, engine states, pilot switch positions, autopilot modes etc.

3.2 Intuition

Following the definition from above, the task of precursor mining is a weakly-supervised task. The only supervision comes from the summary label for a flight that says if it had a safety incident or not. Using this high-level information, the goal is to identify low-level events that occurred during the flight that correlate to the safety incident. Multiple-instance learning is a natural fit for weakly-supervised problems where the bag labels (high-level supervision) are used to infer the instance labels (low-level). Further, a flight spans a finite time and events that happen during a flight are correlated temporally. For example, a flight typically involves dynamics at multiple time scales. An increase in throttle causes a response in engine speed in the order of milliseconds while it takes about 7-10 seconds to cause a notable increase in the airspeed of the flight. Also, when there is a change in wind condition or traffic pattern, it takes much longer to see its effect reflected in the flight’s behavior. Thus it is important to consider instances in the flight along with a context history (seen in the definition of an instance \( e_j^i \)). Figure 2 shows our proposed idea in which each flight is a multidimensional time series with a bag-level label that indicates if the flight had a safety incident or not. Here the instances are defined as the sequence of measurements up to the current time. In this way, an instance at time \( t \) can be thought of as the event that occurs at time \( t \), given the context up to time \( t \). The standard MIL formulation does not capture temporal connection between data instances [13], and we propose a MIL framework that address this problem in the next section.

3.3 The DT-MIL Model

In this section, we develop the deep temporal multiple-instance learning model for precursor mining. Earlier, we defined the time-connected instances \( e_j^i \) by using a history of data measurements. To efficiently model the instances, we use recurrent neural networks with a recently developed sophisticated recurrent unit called the gated recurrent unit (GRU) [8]. Motivated by long short-term memory (LSTM) units, GRUs are proposed as a variant to simplify computation and implementation. Compared to LSTM which has a memory cell and four gating units that adaptively control the information flow inside the unit, the GRU has only two gating units [8]. Owing to its simplicity over LSTM units, we choose GRU as the recurrent units for our model. The information flow in a GRU is shown in Figure 3 while its governing equations are shown below

\[
z_t = \text{sigmoid}(W_z[h_{t-1}, x_t])
\]

\[
r_t = \text{sigmoid}(W_r[h_{t-1}, x_t])
\]

\[
h_t = \tanh(W_s[r_t \cdot h_{t-1}, x_t])
\]

\[
h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t.
\]

The parameters of GRU include \( W_z, W_s \). The reset signal \( r_t \) determines if the previous hidden state should be ignored while the update signal \( z_t \) determines if the hidden state \( h_t \) should be updated with the new hidden state \( \tilde{h}_t \). By having many units each having its own reset and update signals, the GRU learns to capture the dependencies from past data over different time scales [8].

The DT-MIL architecture is shown in Figure 4. The time series data is processed by GRU units which convert the sequence of data into hidden states that are passed on to a layer of fully connected
Nominal flight

Safety incident

$T = 1, 2, \ldots, L$

**Negative Bag**

instance $e_1 : f(x_1)$

instance $e_2 : f(x_1, x_2)$

instance $e_3 : f(x_1, x_2, x_3)$

\[\vdots\]

instance $e_L : f(x_1, x_2, \ldots, x_L)$

**Positive Bag**

Figure 2: Figure showing the idea of a bag representation of a flight with instances corresponding to sequence data up to the current time. A flight is labeled positive if a safety incident is reported.

Figure 3: Figure showing the data flow in a gated recurrent unit (GRU).

$tanh$ units. The recurrent layer captures the temporal dependencies in the data while the fully connected layer adds more approximation capability to the model. Additional recurrent and fully connected layers may be added depending on the requirements. This combination of recurrent and fully connected layers model the deep representation function $f(\cdot)$ in the instance definition in equation (1). The instances $e_t$ are obtained after the fully connected layers which are then fed into a logistic layer to convert the instances into probabilities $p_1, p_2, \ldots, p_t, \ldots, p_L$. The MIL aggregation function $a(\cdot)$ converts the instance probabilities into a bag probability $\hat{y}$ as

$$\hat{y} = a(p_1, p_2, \ldots, p_t, \ldots, p_L).$$

(7)

The loss function for learning is a binary cross-entropy function given by

$$L(y, \hat{y}) = -[y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})].$$

(8)

where $y$ represents the bag label. The above setup can be easily extended to a multi-class case by having many independent logistic layers followed by MIL aggregation layers for each class. It must be noted that multiple logistic layers may be better suited compared to a soft-max layer because a flight may have multiple safety incidents that may not be independent of each other. The model can then be trained using standard backpropagation taking advantage of all the recent advancements made in deep learning including GPU parallelism.

The MIL aggregation is an important function that mimics the MIL assumptions under the cross-entropy loss function. For example, if $a(\cdot)$ is set to a $max(\cdot)$, then it mimics the standard MIL assumption. To see how this works, let the true bag label be 0. To minimize the loss, $\hat{y}$ will be pushed close to 0. Given $\hat{y} = max(p_1, p_2, \ldots, p_t, \ldots, p_L)$ and when $\hat{y}$ is made small, the instance
probabilities $p_1, p_2, \ldots, p_i$, are all pushed close to 0 simultaneously. On the other hand, when the true bag label is a 1, then with the aggregation function being $\max(\cdot)$, at least one of the instance probabilities will be pushed close to 1. Other aggregation functions such as mean, weighted mean, approximated max may be used to reflect different MIL behavior and assumptions.

4 EXPERIMENTS

4.1 Data

For this study, we use the Flight Operational Quality Assurance (FOQA) data provided by a de-identified commercial airline\(^2\) operated between April 2010 to October 2011. Figure 5 shows the airports in Europe where the de-identified airlines operate. The FOQA data consists of most of the sensory measurements on board the aircraft including flight speed, altitude, flight control surfaces, thrust, engine power, fuel consumption, pilot switches, pitch, roll, pressure, temperature among many others. The data is sampled at 1 Hz. Most of the data used in this work are records from flights that takeoff from these airports. To eliminate variability in aircraft characteristics, we consider only the Airbus models A319 and A320 because they belong to the same weight category of interest in this work.

4.2 Safety Incident

Accident statistics [2] show that about half of the fatal accidents happen during the last 4% of the flight - the final approach and landing. One of the key causes of landing related accidents involve energy mismanagement [1], which often lead to loss of control, landing before reaching the runway, runway overrun, hard landing, tail strike etc. The aircraft energy is a function of the weight, airspeed, altitude, thrust, lift and drag forces. One of the primary tasks of the crew is to monitor and control the aircraft’s energy using the throttle, flight path, friction surfaces such as flaps, slats, speed brakes among others.

\[^2\]Owing to proprietary nature of the work, we do not disclose the airline name, data and code to the public.

In this work, we consider the high-speed exceedance (HSE) during landing as the safety incident. The HSE is a rule-based definition for a safety incident that is widely used in operations to analyze safety. HSE is defined as

$$\text{airspeed}_{\text{altitude}=1000\text{ft}} > \text{target} + \text{tolerance} \quad (9)$$

where airspeed and target are recorded as part of the FOQA data. If equation (9) is satisfied, the flight is labeled positive as having the HSE safety event. The label may come from the ASRS reports or from other sources as well. Note that the DT-MIL setup does not require the timestep location of the safety incident. As long as the safety incident is known to have occurred during the flight, it can be labeled positive.

4.3 Model Setup

From our FOQA data, we selected a subset of sensory variables for this study, excluding the ones that were clearly not useful for explaining the HSE event. Some of the continuous variables include airspeed, altitude, angle of attack, speed target, speed reference, aileron position, elevator position, rudder position, stabilizer position, engine speed, pitch angle, roll angle, accelerations along the 3 axes, vertical speed, aircraft gross weight. Some categorical variables include commands on flaps, speed brakes, landing gear, activations of autopilot, autothrottle and various modes of the autopilot, flight director and flight such as flight director engage status, location capture, altitude modes, thrust N1 mode, thrust EPR mode, vertical speed mode, TCAS and STALL status etc [17]. The FOQA data includes over 300 sensory variables out of which we chose a subset of 60 variables based on both domain knowledge and automated feature selection using Granger causality [17].

In about 15 months of operational data, we had about 500 flights that had the HSE event. We sampled the same number of nominal flights. We considered the approach and landing phases of the flight starting approximately 25 nautical miles away from the runway. We sampled the flight sensory data at every quarter nautical mile of ground distance flown until touchdown. Thus, each flight record is about 100 time steps long. Note that the DT-MIL algorithm does not require the time series records to have the same lengths but this was easy to achieve for the current problem. We split the data randomly into training, validation and testing data in proportions 0.5, 0.3, 0.2 respectively. The HSE event is defined based on airspeed and if we choose airspeed as one of the features, then it is possible to get a trivial explanation such as a high airspeed leads to the speed exceedance. To avoid this, we ignored the airspeed and other variables that were highly correlated with airspeed such as ground speed. The data was normalized to center around the mean and have unit variance.

The DT-MIL model was prototyped using Tensorflow. The DT-MIL model architecture is shown in Fig. 4. It includes a GRU recurrent layer with 20 units, a fully connected $\tanh$ layer with 500 units, and a logistic layer to output the instance probabilities. A $\max(\cdot)$ MIL aggregation layer was used to mimic the standard MIL assumption. The model was trained using one GPU on a Dell Precision workstation with 64GB of RAM. The ADAM [19] optimizer with a learning rate of 0.002 was used. An $L_2$ regularization with coefficient 0.0005 was used for all model parameters. The best model was identified by monitoring the performance on the validation data.
5 RESULTS AND DISCUSSION

5.1 Quantitative Results
The models were evaluated using area under the receiver operating characteristic (AUC) score. The DT-MIL model was able to achieve a high accuracy in predicting the HSE event (see Table 1 for bag-level AUC obtained on training and unseen testing data).

Table 1: Area under the ROC curve for bag-level prediction by DT-MIL.

|        | bag-AUC |
|--------|---------|
| DT-MIL | training testing | 0.982 0.967 |

5.2 Instance Probabilities
Using the instance probabilities, the significant events that explain the HSE incident may be identified. Figure 6 shows the instance probabilities for nominal flights and flights with the HSE event for the unseen test data. It can be seen that most of the flights (in both subfigures) start the approach and landing phases from a relatively “safe” state with probabilities close to zero, which is what one would expect. Instances that are about 25 nautical miles from touchdown may be too far out to show significant indications about the HSE incident. As the flights approach the 1000 ft altitude instant where the HSE event is checked, the instance probabilities increase close to 1 (100% likelihood of HSE occurring) for the flights with HSE event (in red), indicating that the instances have information correlating to the HSE event. Such events may be considered as precursors in the explanation task. On the other hand, for the nominal flights (in green), the instance probabilities remain close to zero most of the times, indicating absence of precursors in majority. With the choice of a \( \text{max}(.) \) function for the MIL aggregation, if the instance probability goes above 0.5 at any time during the flight, it will be considered a positive flight. This happens for a few nominal flights which accounts for the false positives. The instances that have a high probability indicate possible precursors even in nominal flights. However, for nominal flights, such precursors are usually followed by corrective actions which decrease the probability close to zero before the HSE checkpoint at 1000ft altitude. This is the case for most nominal flights except for two flights that have a probability higher than 0.5 at the 1000ft altitude checkpoint. In the next section, we explain the HSE events using the precursors and corrective actions inferred from the instance probabilities.

5.3 Safety Incident Explanation
Using DT-MIL, we analyze two flights that had the HSE incident and one nominal flight that was wrongly classified as a HSE flight (false positive).

Figure 7 shows a flight that had the HSE incident. In this flight, up to an altitude of 2700 ft (about 15 miles away from the runway), most variables are within nominal bounds indicating a “safe” state. A few minutes later, the flight made a turn to its final leg. During this time, the usual trend is to reduce the engine command. However, the engine command was increased which caused the engine speed to be higher than normal leading to the flight’s airspeed to remain higher than normal. Owing to the airspeed being high, the flaps were not set. These events are identified as precursors by DT-MIL with corresponding high probability scores. This was corrected when the flight moved close to the outer-marker (5 miles out) which caused the airspeed to decrease, allowing the initial flaps to be set. However, although the airspeed allowed further increase of flaps, around 1500 ft, it was delayed for some unknown reason. Thus, the airspeed remained high at the checkpoint, causing the HSE event. The corresponding probability of DT-MIL indicates this sequence of events.

Figure 8 shows another HSE flight that was explained using DT-MIL precursors. This flight had an aggressive drop in altitude when the flight was between 15 and 10 nautical miles away from the runway. The flight did a roll maneuver along with a steep drop in altitude which caused the airspeed to remain high. Flying involves managing and trading off energy from potential (altitude) to kinetic (airspeed) forms. During landing, energy management is of extreme importance and if not done well, often leads to safety incidents. The aggressive drop in altitude is the main precursor which is followed by a delayed setting of the flaps explains the HSE event for this flight.

To understand false alarms, a nominal flight that was predicted to be positive is analyzed. Figure 9 shows that until about 2000 ft altitude and 5 miles away from the runway, the flight variables were nominal. However, close to the checkpoint, the flaps were not set. Flaps are friction surfaces that are used to control airspeed during landing. The previous examples also show that delaying flaps is one of the main precursors to the HSE incident. In this flight, the
Figure 7: Explanations in the form of precursors identified by DT-MIL for a flight that had a HSE incident. Important events are shown by blue arrows, precursors are marked with red circles while a green star is used to indicate the HSE event.

Figure 8: Explanations in the form of precursors identified by DT-MIL for a flight that had a HSE incident. Important events are shown by blue arrows, precursors are marked with red circles while a green star is used to indicate the HSE event.
flaps were delayed but for some unknown reason (possibly winds, which are not captured in this data), the airspeed remains nominal in spite of the final flaps not set. The DT-MIL model finds this high-risk precursor and gives a high probability value although the HSE event is not flagged in this flight.

6 CONCLUSION
This paper introduces a precursor mining framework for explaining aviation safety incidents. The DT-MIL algorithm extends multiple instance learning to temporal data using deep recurrent neural nets as building blocks. The DT-MIL algorithm is applied to a high speed exceedance safety incident using real flight recorded time series data to find precursors and build an explanation for the adverse event. Future work will involve extending the DT-MIL framework to analyze multiple safety incidents and formulate flight safety margins using this method.

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