Airplane Accidents Predictive Using AI and Machine Learning Programming

Abstract

Our invention Airplane Accidents Predictive Using AI and Machine Learning Programming is a analyzing flight data using predictive models and a quadratic least squares model is applied to a matrix of time-series flight parameter data for a flight, thereby deriving a mathematical signature for each flight parameter of each flight in a set of data including a plurality of sensor readings corresponding to time-series flight parameters of a plurality of flights. The invention is also the derived mathematical signatures are aggregated into a dataset and a similarity between each pair of flights within the plurality of flights is measured by calculating a distance metric between the mathematical signatures of each pair of flights within the dataset, and the measured similarities are combined with the dataset. The invention is also including a machine-learning algorithm is applied to the dataset, thereby identifying, without predefined thresholds, clusters of outliers within the dataset by using a unified distance matrix. The invention is also including a considering the immense cost of air crashes, the study examines the causes of crashes of aircrafts based on reported findings for the crash and the dataset used for this study included data for all reported air crashes across the globe for the period from 1971 to 2020. The invention is also considering Multiple machine learning algorithms were used to identify the best for predicting the likely cause of accident based on features available and the Machine Learning Models used are Auto Classifier, Tree-AS and Gboost. 11 fPredictive Pricing 300 \Detenminer Routine 305 Obtain historical price information 310 Analyze information to determine predictive pingnformation based on the hisorialinformation * 315 Store/update determined predictive pricing information Continue? 399 End FIG. 11s a flow diagram of an embodiment of a Predictive Pricing Determiner routine.

Classifications

G06F17/16 Matrix or vector computation, e.g. matrix-matrix or matrix-vector multiplication, matrix factorization

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Inventor: Krushnadeo Tanaji Belerao, Chordiya, (Dr.) S. B., Darshana Desai, Yagya Dutta Dwivedi, Akhtar Husain, C. Joshi, Ashutosh Eknath Khedkar, Laxman Singh, Gaurav Tripathi, Sanjay Kumar

Current Assignee : Belerao Krushnadeo Tanaji Dr , Desai Darshana Dr , Dwivedi Yagya Dutta Dr , Husain Akhtar Dr , Khedkar Ashutosh Eknath Prof , Kumar Sanjay Dr

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Info: Legal events, Similar documents, Priority and Related Applications

External links: Espacenet, Global Dossier, Discuss

Claims (4)

Hide Dependent

WE CLAIM

1) Our invention Airplane Accidents Predictive Using AI and Machine Learning Programming is an analyzing flight data using predictive models and a quadratic least squares model is applied to a matrix of time-series flight parameter data for a flight, thereby deriving a mathematical signature for each flight parameter of each flight in a set of data including a plurality of sensor readings corresponding to time-series flight parameters of a plurality of flights. The invention is also the derived mathematical signatures are aggregated into a dataset and a similarity between each pair of flights within the plurality of flights is measured by calculating a distance metric between the mathematical signatures of each pair of flights within the dataset, and the measured similarities are combined with the dataset. The invention is also including a machine learning algorithm is

applied to the dataset, thereby identifying, without predefined thresholds, clusters of outliers within the dataset by using a unified distance matrix. The invention is also including a considering the immense cost of air crashes, the study examines the causes of crashes of aircrafts based on reported findings for the crash and the dataset used for this study included data for all reported air crashes across the globe for the period from 1971 to 2020. The invention is also considering Multiple machine learning algorithms were used to identify the best for predicting the likely cause of accident based on features available and the Machine Learning Models used are Auto Classifier, Tree-AS and Gboost.

2) According to claim1,2# the invention is to an analyzing flight data using predictive models and a quadratic least squares model is applied to a matrix of time-series flight parameter data for a flight, thereby deriving a mathematical signature for each flight parameter of each flight in a set of data including a plurality of sensor readings corresponding to time-series flight parameters of a plurality of flights.

3) According to claiml,2,3# the invention is to the derived mathematical signatures are aggregated into a dataset and a similarity between each pair of flights within the plurality of flights is measured by calculating a distance metric between the mathematical signatures of each pair of flights within the dataset, and the measured similarities are combined with the dataset.

4) According to claiml,2,3,4# the invention is to a machine-learning algorithm is applied to the dataset, thereby identifying, without predefined thresholds, clusters of outliers within the dataset by using a unified distance matrix.

) According to claiml,2,4,6# the invention is to a considering the immense cost of air crashes, the study examines the causes of crashes of aircrafts based on reported findings for the crash and the dataset used for this study included data for all reported air crashes across the globe for the period from 1971 to 2020. 6) According to claim1,2,4,5# the invention is to an considering Multiple machine learning algorithms were used to identify the best for predicting the likely cause of accident based on features available and the Machine Learning Models used are Auto Classifier, Tree-AS and Gboost.

FIG. 1is a flow diagram of an embodiment of a Predictive Pricing Determiner routine.

FIG.2: Monitoring Data Base

FIG.3: Avoidance the Status

FIG.4: Cloud Status

Description

fPredictive Pricing 300 \Detenminer Routine

305

Obtain historical price information

310 Analyze information to determine predictive pingnformation based on the hisorialinformation

* 315 Store/update determined predictive pricing information

Continue?

399 End

FIG. 11s a flow diagram of an embodiment of a Predictive Pricing Determiner routine.

Airplane Accidents Predictive Using AI and Machine Learning Programming

FIELD OF THE INVENTION

Our invention is related to an airplane accidents predictive using AI and machine learning programming

BACKGROUND OF THE INVENTION

Federal Aviation Administration (FAA) and other regulatory agencies have relied on reactive measures to attempt to ensure safe practices in the National Airspace Systems (NAS). However, reactive analysis does not circumvent most safety issues, as reactive analysis is often employed after an event has occurred. Industry experts are now advocating proactive measures, which may identify accident precursors to mitigate risks. However, several considerations impede this analysis. First, the disparate nature of flight, telemetry, and maintenance data presents dimensionality challenges. Second, accumulated flight, telemetry, and maintenance data often requires large-scale data analysis and scalable solutions. Finally, identifying risks in flight, telemetry, and maintenance data can be difficult.

In many situations, potential buyers or other acquirers of various types of items (such as products and/or services) are faced with difficult decisions when attempting to determine whether acquiring a particular item of interest under current conditions is desirable or optimal based on their goals, or whether instead delaying the acquisition would be preferable.

For example, when the potential acquirer desires to obtain the item at the lowest price possible before some future date, and the item is currently offered by a seller for a current price, the potential acquirer needs to evaluate whether accepting the current price is more advantageous than the potential benefits and costs associated with waiting to see if the item will continue to be available and will be later offered at a lower price before the future date. Such potential acquisitions can include a variety of types of transactions (e.g., fixed-price purchase, auction-based purchase, reverse auction purchase, name-your-price purchase, rent, lease, license, trade, evaluation, sampling, etc.), and can be performed in a variety of ways (e.g., by online shopping using a computing device, such as via the World Wide Web or other computer network).

The difficulty of evaluating a potential current item acquisition is exacerbated in environments in which the prices of the items frequently change, such as when sellers or other suppliers of the items frequently modify item prices (e.g., in an attempt to perform yield management and maximize overall profits). In such environments, the likelihood of future price changes may be high or even a certainty, but it may be difficult or impossible for the potential acquirer to determine whether the future price changes are likely to be increases or drops, let alone a likely magnitude and timing of such changes. A large number of types of items may have such frequent price changes, such as airline tickets, car rentals, hotel rentals, gasoline, food products, jewelry, various types of services, etc. Moreover, a potential acquirer may in some situations need to evaluate not only a current price of an item of interest from a single seller or other provider, but may future need to consider prices offered by other providers and/or prices for other items that are sufficiently similar to be potential substitutes for the item of interest (e.g., airline flights with the same route that leave within a determined period of time, whether from the same airline or from competitor airlines).

In a similar manner, some sellers or other providers of items may similarly face difficulties in determining an advantageous strategy related to the providing of the items, such as for intermediary sellers that must acquire an item from a third party supplier (e.g., an original supplier of the item or other intermediary seller) before providing it to a customer. For example, it may be difficult in at least some situations for such intermediary sellers to know what price to offer to customers in order to maximize profit, as well as whether to immediately acquire from a third-party supplier an item purchased by a customer or to instead delay such an acquisition in an attempt to later acquire the item at a lower price.

In the context of the airline industry, for example, such intermediary sellers may include various types of travel agents, including travel agents that typically buy only single airline tickets in response to explicit current instructions from a customer, consolidators that buy large numbers of airline tickets in advance for later resale, tour package operators that buy large numbers of airline tickets for bundling with other tickets and/or services, etc.

Airplanes are being used as a mode of transportation by millions of people on a daily basis. The invention of airplanes has done a lot of good as it is used by people for a plethora of purposes be it for travelling to exotic places, for business meetings, or just to meet with one's family members or friends. The airplanes are getting popular as a means of transportation amongst people by the day mostly due to the fact that they are the fastest mode of transportation available. Also, people's jobs nowadays are pretty tedious and demanding and time efficiency is a very essential factor to stay competitive among one's colleagues. Apart from this, aviation has proved to be the safest mode of transportation. Generally speaking, a person is more likely to die in a car accident than in a plane accident because the rate of aviation accidents is much lesser than car accidents.

However, it is true that the chances of surviving a car accident are much better than in a plane accident as the results of an airplane crash may result in catastrophic numbers of death. Since the first flight by the Wright Brothers there has been a substantial improvement in the technologies and machineries which have contributed to making the planes a lot safer than they used to be. Even though airplanes have their own advantages, they do come with their fair share of disadvantages and problems. One of the cons that airplanes have is that they consume enormous amounts of fossil fuel which pose a great threat to environmental reserves of fossil fuels. In addition to this, the airplanes when burn large amounts of fuel also play a major role in polluting the environment.

OBJECTIVES OF THE INVENTION

1. The objective of the invention is to a analyzing flight data using predictive models and a quadratic least squares model is applied to a matrix of time series flight parameter data for a flight, thereby deriving a mathematical signature for each flight parameter of each flight in a set of data including a plurality of sensor readings corresponding to time-series flight parameters of a plurality of flights. 2. The other objective of the invention is to the derived mathematical signatures are aggregated into a dataset and a similarity between each pair of flights within the plurality of flights is measured by calculating a distance metric between the mathematical signatures of each pair of flights within the dataset, and the measured similarities are combined with the dataset. 3. The other objective of the invention is to machine-learning algorithm is applied to the dataset, thereby identifying, without predefined thresholds, clusters of outliers within the dataset by using a unified distance matrix. 4. The other objective of the invention is to considering the immense cost of air crashes, the study examines the causes of crashes of aircrafts based on reported findings for the crash and the dataset used for this study included data for all reported air crashes across the globe for the period from 1971 to 2020. 5. The other objective of the

invention is to considering Multiple machine learning algorithms were used to identify the best for predicting the likely cause of accident based on features available and the Machine Learning Models used are Auto Classifier, Tree-AS and Gboost.

SUMMARY OF THE INVENTION

The following description and the drawings sufficiently illustrate specific embodiments to enable those skilled in the art to practice them. Other embodiments may incorporate structural, logical, electrical, process, and other changes. Portions and features of some embodiments may be included in, or substituted for, those of other embodiments. Embodiments set forth in the claims encompass all available equivalents of those claims.

As used in this patent application, the term "flight data" may include, but is not limited to, data acquired from flights of manned and unmanned aircraft, telemetry data, and aircraft maintenance data.

Statistics show that many accidents/incidents in aviation have causes which are recurrent. Therefore, strategies can be employed to learn from flight data to identify accident precursors to mitigate potential safety hazards. Predictive data mining identifies patterns and detects trends through clustering, classification, or regression analysis.

Onboard flight data also includes certain mechanical status information, such as fuel flow, exhaust gas temperature, oil pressure, etc. This data, if analyzed properly, may give indications of mechanical statuses such as current engine compression ratios and impending irregularities and failures such as engine failures, electrical system abnormalities, and valve malfunctions. A system capable of analyzing this data may give an early-warning and risk- free (without taking flight) notice to aircraft operators that a mechanical problem is likely to occur in the near future. The operator could then address the problem prior to the aircraft taking flight and prevent a mechanical anomaly from occurring.

As data collection continues to experience exponential growth and the cost of large-scale storage devices becomes cheaper, there is an abundance of data from which a wealth of knowledge can be obtained. Data mining is the process of exploring data to predict new situations, discover meaningful patterns and detect trends in data. Several industries have benefitted from the use of data mining techniques, as it is able to explore the intricacies of complex systems and explain underlying phenomena.

In aviation, aircraft that are equipped with a flight data recording capability or device, such as a Flight Data Recorder (FDR) or a Quick Access Recorder (QAR), record hundreds, and sometimes thousands, of flight and mechanical parameters at various time intervals. This data may hold key information regarding the aircraft's operations during various phases of flight, and may be used to identify unsafe practices and violations of standard operating procedures. One approach used to collect and analyze such data includes Flight Data Monitoring (FDM) or Flight Operations Quality Assurance (FOQA). FDM/FOQA is a methodology for collecting and analyzing flight data to proactively identify anomalies and mitigate risks associated with unsafe practices. The FDM/FOQA process includes four main steps:

BRIEF DESCRIPTION OF THE DIAGRAM

FIG. 11s a flow diagram of an embodiment of a Predictive Pricing Determiner routine. FIG.2: Monitoring Data Base FIG.3: Avoidance the Status FIG.4: Cloud Status

DESCRIPTION OF THE INVENTION

Also, airplanes are greatly affected by environmental conditions. It gets particularly difficult to navigate and control an airplane in bad weather. Strong winds cause turbulence; fog causes visual hindrance as well. Also the chances of surviving an aviation accident are almost close to zero. The most common reasons for aviation accidents are mentioned below:

1. Mechanical Faults: Since airplanes are unequivocally very complex machines there certainly persists a chance of some equipment failing to work as expected. Even if there is a malfunctioning of a small component, it may lead to a chain reaction of things going wrong which eventually may lead to loss of control of the aircraft resulting in major airplane accidents.

2. Pilot & Crew Error: It is one of the most frequent causes of airplane wrecks. Airplanes are unquestionably very complex feats of engineering and flying them is not a simple task either. It requires a great amount of precision and concentration while operating an airplane. There are a lot of gauges as well as handouts that have to be read and understood. Even a minor error while reading or understanding them can lead to major failures resulting in fatal crashes. So a pilot has to work in an extreme amount of pressure with utmost sincerity.

3. Environmental Conditions: Environmental conditions certainly play a role in airplane accidents. Since an airplane flies at very high altitudes if the weather deteriorates it becomes very difficult to control the airplane. If there's fog in the environment it becomes difficult to navigate midair. Also, if there are gale winds in the environment the airplane may experience turbulence resulting in loss of controls. It is also seen that many of the plane crashes are a result of a lightning strike on the plane resulting in major equipment going haywire. Unlike other vehicles, airplanes can't be immediately put to a halt if certain conditions are encountered as they need a suitable runway to land. 4. Air Traffic Control Errors: Sometimes there may be an accident due to the error made not by the pilot and his crew but instead by the air traffic controller communicating with them. It is not unheard of that an air traffic controller was overworked and dozed off at the time of duty or he/she made an error while helping the pilots navigate their way back to the airports resulting in airplane crashes. 5. Other Factors: Apart from the above mentioned reasons there are some other factors that have contributed to airplane crashes in the past. One of these reasons is war. During war, the planes have been shot down by ground missiles causing them to crash. Also, if a plane has accidentally flown into anti-aircraft zones they are shot at. Apart from these factors, it's seen that terrorist attacks and hijacking has also played a role in airplane crashes such as the attack on the world trade center, USA. Sometimes, airplanes are sabotaged by terrorist organizations as well. In addition to all these reasons, some other reasons although very rare are the pilots fainting or dying on the airplane due to medical reasons, pilots being mentally ill trying to crash the airplanes, some passengers trying to attempt suicide jeopardizing other lives as well.

There are three types of machine learning strategies: supervised, unsupervised and reinforcement learning. Supervised learning, also called classification, is the process of finding a suitable training set that classifies new problems, whose label is unknown. Examples of classification techniques include decision tree induction, Bayesian networks, k-nearest neighbor, and support vector machines. In unsupervised learning, also called clustering, the algorithm is provided with unlabeled data that it uses to group items based on their similarity with each other. Clustering techniques include k-means, fuzzy c- means, and Density Based Spatial Clustering of Applications with Noise (DBSCAN). Reinforcement learning operates on a merit system and its course of actions is determined by what yields the greatest reward. However, reinforcement learning is rarely applied in practical data mining.

Mining GA flight data poses many challenges. First, the flight parameters recorded by the FDR/QAR varies by the model of aircraft; the number of parameters recorded ranges from a minimum of one parameter to over 2000 parameters. In the case of UAS flight, a separate data/telemetry package file may be created for each UAS flight, and the data may be streamed as a part of the command and control link. Second, flight data may consist of discrete and continuous time series data, which are recorded at various time intervals.

Therefore, data dimensionality issues may occur. Finally, analyzing and reducing the dimension of data without losing potentially critical information may be very difficult.

An Artificial Neural Network (ANN) is a mathematical model that mimics the structure and behavior of a biological neural network. ANNs are represented as a directed graph of interconnected neurons. Neurons, also called nodes or processing units, influence each other using weighted connections; positive weights have stimulating influence, while negative weights have inhibiting influence. ANNs can be effectively used for classification, clustering, forecasting, pattern recognition, and dimension reduction.

ANNs possess several advantages, including a high level of accuracy and efficiency, noise tolerance, ability to process large-scale data, speed, and adaptability. Their disadvantages may include the inability to determine the optimal number of neurons, and difficulty in selecting a training set that is representative of the problem to be solved. The effectiveness of neural networks lies in their ability to learn and classify data without being influenced by invalid data, as the learning process allows for adjustments to any bias incurred. However, a large amount of erroneous data will affect the quality of the overall solution.

Embodiments discussed herein may use various machine-learning techniques, such as Support Vector Machines ("SVM"s), predictive neural networks, self organizing maps ("SOM"s), etc. SOMs are a special class of artificial neural networks that project high dimensional data into a low dimensional feature space. SOMs can be effectively used in the exploratory phase of data mining to visualize and explore the properties of data, while preserving the data topology. This means that the relationship between data is preserved, as they will be mapped within close proximity if they are related and will be sensitive to similar inputs in the model. SOMs consist of an input and an output layer, which is organized in a lattice.

Inputs are influenced by weights, which tune the lattice using an unsupervised competitive learning process. After training completes, the SOM is able to classify new data using the tuned lattice and the knowledge acquired in the learning phase.

An outlier, or an atypical flight, may indicate the presence of an error or may be a precursor for an accident. Detecting outliers may assist in predicting the conditions, under which an accident may occur. Current technologies for flight aviation safety/data mining use fixed exceedances, where an error is flagged only if a certain value exceeds a set error threshold. Various embodiments use neural network technology to learn which values are outliers, and form connections between different pieces of data to offer a more robust detection of errors and outliers.

For example, three flight data values may not be above the set exceedances that would normally flag as an error; however, if all three were close to those values, the neural network can learn that this is still unusual activity and detect an error because of the combination of those three values. Furthermore, some embodiments may be used to compare flights with different recorded parameters.

FIG. 1 is a flow diagram of an embodiment of a Predictive Pricing Determiner routine 300. The routine begins at step 305, where historical pricing information is obtained for one or more items, and continues to step 310 to analyze the data to determine predictive pricing information based on the historical data. In step 315, the routine then stores or updates previously stored predictive pricing information from the analysis in step 310. After step 315, the routine continues to step 395 to determine whether to continue. If so, the routine returns to step 305, and if not the routine continues to step 399 and ends.

Similar Documents

Publication	Publication Date	Title
US10248742B2	2019-04-02	Analyzing flight data using predictive models
Zhang et al.	2019	Ensemble machine learning models for aviation incident risk prediction
Matthews et al.	2013	Discovering anomalous aviation safety events using scalable data mining algorithms
Mangortey et al.	2020	Application of machine learning techniques to parameter selection for flight risk identification
Zhang et al.	2015	A integrated vehicle health management framework for aircraft—A preliminary report
Puranik et al.	2020	Identification of instantaneous anomalies in general aviation operations using energy metrics
Li et al.	2017	Civil aircraft big data platform
Puranik et al.	2020	Towards nline prediction of safety-critical landing metrics in aviation using supervised machine learning
Lee et al.	2021	Data-driven system health monitoring technique using autoencoder for the safety management of commercial aircraft
Lee et al.	2020	Critical parameter identification for safety events in commercial aviation using machine learning
Burmester et al.	2018	Big data and data analytics in aviation
Ackley et al.	2020	A supervised learning approach for safety event precursor identification in commercial aviation
Lee et al.	2021	Deep spatio-temporal neural networks for risk prediction and decision support in aviation operations
Li et al.	2020	Analysis of operational and mechanical anomalies in scheduled commercial flights using a logarithmic multivariate Gaussian model
Calle-Alonso et al.	2019	A Bayesian-network-based approach to risk analysis in runway excursions
AU2021101256A4	2021-05-06	Airplane Accidents Predictive Using AI and Machine Learning Programming
Kang et al.	2020	A deep sequence-to-sequence method for aircraft landing speed prediction based on QAR data
Chin et al.	2019	Phases of flight identification for rotorcraft operations
Ortiz et al.	2008	Multi source data integration for aircraft health management
Mangortey	2019	Predicting the occurrence of ground delay programs and their impact on airport and flight operations
Martınez et al.	2019	Forecasting Unstable Approaches With Boosting Frameworks and LSTM Networks
Christopher et al.	2013	Data mining approaches for aircraft accidents prediction: An empirical study on Turkey airline
Mathur et al.	2017	Prediction of aviation accidents using logistic regression model
Barry	2021	Estimating runway veer-off risk using a Bayesian network with flight data
Jharko et al.	2016	On creating safety control systems for high operation risk plants

Priority And Related Applications

Priority Applications (1)

Application	Priority date	Filing date	Title
AU2021101256A	2021-03-10	2021-03-10	Airplane Accidents Predictive Using AI and Machine Learning Programming

Applications Claiming Priority (1)

Application	Filing date	Title
AU2021101256A	2021-03-10	Airplane Accidents Predictive Using AI and Machine Learning Programming

Legal Events

Date	Code	Title	Description
2021-05-06	FGI	Letters patent sealed or granted (innovation patent)	

Concepts

machine-extracted

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Name	Image	Sections	Count	Query match
machine learning		title,claims,abstract,description	19	0.000
flight		claims,abstract,description	67	0.000
matrix material		claims,abstract,description	8	0.000
diagram		claims,abstract,description	6	0.000
corresponding		claims,abstract,description	4	0.000

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