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Exploration of Natural Language Processing (NLP) Applications in Aviation

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As a result of the tremendous boost in computational power, the current prevalence of large bodies of data, and the growing power of data-driven algorithms, natural language processing (NLP) has recently experienced rapid progressions in multitudinous domains, one of which is aviation. In this study, we explore the current standing of NLP in aviation from the perspective of both research and industry. We identify safety reports analyses, aviation maintenance, and air traffic control as the three main focus areas of NLP research in aviation. We also list currently available NLP software and how they have been used in the aviation industry. Finally, we shed a spotlight on some of the existing challenges posed by the aviation domain on standard NLP techniques, discuss the current corresponding research efforts, and put forward our recommended research direction.

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Introduction

Natural language processing (NLP) is a subfield of artificial intelligence that deals with the computational processing of human or natural language. It is concerned with analyzing text or speech to automatically perform tasks like text classification, information retrieval, sentiment analysis, document summarization, and machine translation, ultimately leading to natural language understanding and natural language generation. With the growing capacity to gather enormous volumes of data, the continuous development of powerful data-driven algorithms, and the substantial increase in computational power, NLP has recently made giant strides in a wide variety of domains (Kalyanathaya et al., 2019; Roadmap, 2020), one of which is aviation.

The purpose and contribution of this study are to explore and synthesize the recent applications of NLP in the aviation domain. We opted for applications from 2010 through 2022 and used search terms like “NLP,” “NLP in aviation,” and “NLP software in aviation” to narrow down search results. Specifically, our study identifies three areas of application in aviation into which NLP research has been making inroads. The study also provides a list of existing NLP software and their current applications in the aviation industry. Lastly, we briefly discuss some of the current challenges faced by NLP in aviation and prospective future research directions.

NLP Research in Aviation

This section presents three application areas of NLP research in aviation: safety reports, aviation maintenance, and air traffic control. For each area, we provide a brief introduction followed by a summary of the research that has recently been ongoing.

Safety Reports

In aviation, an incident refers to any abnormal event that has either compromised the general safety of aviation operations (Tanguy et al., 2016) or could have progressed into an accident but did not. Incidents occur much more frequently than actual accidents (Dong et al., 2021; Tanguy et al., 2016). Reporting systems exist where people report the incidents or accidents as well as access their probable causes and risks (Buselli et al., 2021; Rose et al., 2020; Tanguy et al., 2016). These reports serve as an invaluable source of data whose quantitative analysis conduces to insightful statistics (Buselli et al., 2021; Dong et al., 2021; Tanguy et al., 2016) and can be used to uncover underlying trends (Kierszbaum & Lapasset, 2020; Tanguy et al., 2016), patterns, and anomalies (Rose et al., 2020). The reporting systems permit the early discovery of potential threats to aviation safety so that preventative measures may be taken (Buselli et al., 2021; Dong et al., 2021; Tanguy et al., 2016). These systems may be used to pinpoint and examine the leading and contributory factors that culminate in the incident or accident, substantially paving the way for better-informed operational decisions and firm prevention plans (Dong et al., 2021; Tanguy et al., 2016).

From a pragmatic perspective, experts and safety managers need to briefly characterize each of the reports to realize analytical tasks on safety reports, generally through their manual assortment according to predefined taxonomies (Pimm et al., 2012; Tanguy et al., 2016). The process of manual categorization is inherently quite complex, error-prone, and resource-consuming (Buselli et al., 2021; Marev & Georgiev, 2019; Pimm et al., 2012; Tanguy et al., 2016). This is not only because of the breadth and perplexity of the taxonomies but also due to the increasing number of reports submitted (Buselli et al., 2021; Pimm et al., 2012; Tanguy et al., 2016) in correspondence to the expansion of commercial and private aviation industries (Dong et al., 2021). In consequence, a legitimate pressing demand for automating the analysis of incident and accident reports has risen (Buselli et al., 2021). Since the reports are in the form of free text written in natural language, with a few of them also incorporating supporting metadata presented in a predetermined, usually tabular, format (Buselli et al., 2021; Dong et al., 2021; Kierszbaum & Lapasset, 2020; Klein et al., 2021), advanced NLP techniques have recently been employed in this automation process (Marev & Georgiev, 2019; Tanguy et al., 2016).

Text Classification

One of the principal research directions has been to apply text classification techniques to categorize reports according to the cause of the incident or accident, making use of preset labels either extracted from existent taxonomies (Tanguy et al., 2016; Tulechki, 2015) or manually annotated by domain experts (Buselli et al., 2021). Such a classification problem (either single-label or multi-label) has been frequently tackled by training supervised machine learning (SML) models, like the support vector machines used by Tanguy et al. (2016), to associate each report with the appropriate label. A fundamental issue with SML algorithms is their reliance on the availability of large, labeled datasets for adequate training. To address this issue, Dong et al. (2021), Klein et al. (2021), and Marev & Georgiev (2019) attempted not to train a classification model from scratch but to utilize a well-trained language model (LM), like the RoBERTa model (Liu et al., 2019). They further fine-tuned the model for the classification task at hand, exploiting what the LM has already learned from its thorough pre-training on huge corpora of textual data. A different approach to handling the problem of scarce labeled training datasets was adopted by Madeira et al. (2021). They proposed a semi-supervised label spreading algorithm (Zhou et al., 2003) that propagates labels from the limited labeled dataset to the much larger mass of untagged data.

Topic Modelling

Even with a pre-trained language model or a semi-supervised learning technique, an immanent deficiency in the text classification process itself persists; it inherently cuts down on the amount and variety of information that can be extracted from reports and reduces the patterns that can be detected within the data (Buselli et al., 2021). This is because it relies on a fixed set of labels in a dynamic environment where new technological innovations emerge each day, calling for a more adaptive approach that is capable of detecting the novel risks introduced as a consequence (Pimm et al., 2012; Tanguy et al., 2016). The restrictiveness of the labels also stems from the fact that they are normally too broad to capture slight variations between events (Tanguy et al., 2016). On these grounds, Buselli et al. (2021), Kuhn (2018), Robinson (2019),

Rose et al. (2020), and Tanguy et al. (2016) opted for topic modeling, an unsupervised clustering-based approach that infers a chosen number of categories, or topics, from the narratives of the reports themselves such that more than one topic can be identified in a single report. By tailoring the number of topics to be extracted by the model, the resulting categories can be as generic or as specific as necessary (Tanguy et al., 2016), thus revealing disparate levels of knowledge without the need for prior labeling.

Other Approaches

It can be argued that the very nature of causal factor categories, regardless of using supervised or unsupervised methods, dictates a compromise between expressiveness, which too basic categories lack, and feasibility, put at stake by fine-grained categories, which demand much more expensive computations (Pimm et al., 2012). On that account, a different approach to automatically analyzing incident and accident reports was proposed by Pimm et al. (2012) and Tanguy et al. (2016), where, given a new report, they identified and pulled out from the database other reports sharing similar characteristics. They measured content similarity and maximum lexical overlap between the new report and all others; thus, providing insights about whether the underlying event is happening for the first time, is rare with only a few similar occurrences in the past, or is recurring and perhaps fits in a wider trend. Another approach was presented by Zhang et al. (2021), who aimed to spot patterns in sequences of events and learn their associations with possible adverse consequences. They are used as input either event sequences noted from accident investigation reports or the raw text narratives representing them into a long short-term memory (LSTM) neural network. The network captured long-term temporal dependencies and predicted whether an accident or an incident would eventuate, whether the aircraft would be damaged, and whether fatalities would be likely.

Aviation Maintenance

Aircraft maintenance, repair, and overhaul (MRO) operations are of the most critical in the aviation industry owing to their utmost cruciality to aviation safety and aircraft performance. Two of the main applications that NLP has found in aircraft maintenance are the support of the switch to predictive maintenance and providing MRO technicians with assistance in the maintenance procedures themselves.

The primary objective of predictive maintenance is determining the ideal time for performing maintenance (Akhbardeh et al., 2021; Carchiolo et al., 2019) such that it is not as late as with reactive approaches or as frequent as preventative ones. Reactive approaches wait for components to fail and then repair them. Preventative actions require adherence to a fixed, overly precautionary schedule (Selcuk, 2017). Consequently, predictive maintenance boosts safety as well as enhances operational efficiency by eliminating unplanned component downtime (Dangut et al., 2021) and repair time, all while reducing costs by avoiding unnecessary inspections (Carchiolo et al., 2019). To determine the optimal time for maintenance, informed predictions of foreseeable faults and component failures are to be made early enough such that maintenance can be performed before any malfunctions occur (Dangut et al., 2021). These predictions are based on extensive analyses of historical maintenance logbooks (Dangut et al., 2021), which contain records of past maintenance issues (Akhbardeh et al., 2020) with noted details about the time,

type, and causes of component failures, a description of the faulty part (Dangut et al., 2021), and a summary of the repairing operation (Carchiolo et al., 2019). The classification of those records is essential to realizing predictive maintenance systems (Akhbardeh et al., 2021), and, for the reasons discussed in the section on Safety Reports, its automation is vital. One of the most prevalent challenges encountered in the automation process is the inherent imbalance in maintenance records (Akhbardeh et al., 2021; Dangut et al., 2021; Usuga-Cadavid et al., 2021); instances belonging to classes describing certain causes for maintenance substantially outnumber those belonging to others resembling much rarer factors (Dangut et al., 2021). Akhbardeh et al. (2021) investigated the classification of technical issues described in maintenance logbook records using a deep neural network (DNN) (Dernoncourt et al., 2017), an LSTM neural network (Suzgun et al., 2019), a recurrent neural network (RNN) (Pascanu et al., 2013), a convolutional neural network (CNN) (Lin et al., 2018), and a pre-trained BERT (Devlin et al., 2018). They considered several techniques for handling the class imbalance problem and established the superiority of the feedback loop strategy. The aim of Dangut et al. (2021) was to leverage the history of logged component failures to predict, using NLP techniques (TF-IDF and Word2vec) and ensemble-learning, future breakdowns of a certain component (binary classification) or of all components (multi-class classification). Since logbook entries corresponding to actual component failures are remarkably rare compared to ones describing routine maintenance (Dangut et al., 2021), they opted for overcoming the imbalance problem through exploring patterns only in this minority class. The objective of Usuga-Cadavid et al. (2021) was to exploit maintenance logs to tackle three classification problems: whether an unplanned failure will occur (binary classification), how long will the breakdown take (multi-class classification), and what will the cause of this failure be (multi-class classification). They compared the performance of transformer-based models, CamemBert (Martin et al. 2020) and FlauBERT (Le et al. 2020), with that of classic machine learning models. They also experimented with different data-level and algorithm-level techniques for mitigating the effect of class imbalance and found that the random oversampling (ROS) technique was the most convenient when computational complexity was not an issue.

When MRO technicians, especially new or less experienced ones, are carrying out their operations, they tend to occasionally turn to maintenance textbooks and manuals or more experienced technicians for instructions, inquiries, and guidance. Hence, Abdullah & Takahashi (2016) worked on creating an easily queried Wisdom Knowledge Database from past maintenance records and daily reports, which they categorized according to the described maintenance operation using an ontology-based semantic classification rule engine that they developed. Besides written documents, they video-recorded senior technicians while executing the different maintenance operations, extracted the voice from the videos, performed speech-to-text conversion using the iSpeech API (2007), classified the output text in the same sense, and lastly incorporated the corresponding videos into the database. Alternately, Integrated Electronic Technical Publications (IETP) combine maintenance-related documentation from various sources for convenient consultation by technicians while undergoing their MRO operations (Marques et al., 2021). For the sake of reducing the time it takes to retrieve relevant IETPs, Marques et al. (2021) proposed an interactive voice search tool using voice recognition and information retrieval techniques, allowing MRO technicians to readily access the desired publications through voice commands.

Air Traffic Control

For seamless navigation of flights to their intended destinations, air traffic controllers (ATCOs) provide pilots with the requisite guidance by means of communicating, primarily through speech (Badrinath & Balakrishnan, 2022), real-time traffic information (Lin, 2021; Sun & Tang, 2021). The smoothness of air traffic, and hence flight safety, critically rely on the accuracy, effectiveness, and promptness of this communication (Sun & Tang, 2021). Accordingly, research in air traffic control (ATC) largely focuses on eliminating communication errors and assisting ATCOs and pilots in fully and more easily comprehending the verbal messages they exchange (Lin, 2021). For instance, Abdullah et al. (2017) suggested that an automatic categorization of incoming messages can be of great help to both parties. They proposed converting communicated speech into text and then assigning it to its semantically relevant category using a knowledge-based approach. Besides following an end-to-end speech recognition architecture in developing an automatic speech recognition (ASR) model that is adapted to the ATC domain, Badrinath & Balakrishnan (2022) aimed at using NLP techniques on the generated transcripts of ATC communications to extract key operational information: the runway number associated with each flight and the call-sign uniquely identifying it. While adopting a rule-based grammar approach in extracting runway information, they used a named entity recognition (NER) model that is based on a deep CNN in classifying word sequences in the unstructured transcripts into categories representing the different call signs. Sun & Tang (2021) proposed monitoring ATC communications and raising alerts when a communication error is probable, thus, lowering the chance of losses of separation (LoS) where distances between aircraft in controlled airspace fall below the allowed minimum. They estimated not only the conditional probabilities of different types of communication errors based on key features of the communication but also the probability of LoS given those error types. To determine the communication features, the researchers first transcribed the ATC communications using IBM Watson Speech-to-Text (IBM, 2018) and then used NLP tools like LinguaKit (2018) and Cortical.io (2011) to extract features such as the number of words per message and whether there is a reference to a certain speed, altitude, or direction. From a slightly different angle, Wang et al. (2019) suggested that erroneous ATCO instructions resulting in conflicts can be recognized in advance by analyzing each of the instructions and predicting corresponding future trajectories. To facilitate the automation of this analysis, Wang et al. (2019) proposed that ATCO commands follow a certain structured template, and they provided a method of transforming complex unstructured control messages into simple structured ones. This method included ASR of spoken ATC commands followed by the application of NLP techniques like semantic role labeling and NER to semantically analyze the resulting transcript and eventually obtain the structured instruction.

NLP Software Products in the Aviation Industry

There are software companies currently offering NLP solutions aimed at automating the process of text analysis in disparate industries. Software tools that are specifically tailored to serve the aviation industry are not sufficiently prevalent, but they are growing in number. In this section, we highlight a representative sample of those software tools, whether provided by institutions that are primarily concerned with the aviation domain or by companies that develop solutions for several industries, one of which is aviation.

Some companies do not target one specific application area in aviation; they instead develop several general-purpose products that handle major text analytics tasks in NLP and can be incorporated into different solutions. Among those companies are IBM with its IBM Watson (IBM, 2010), Algodom Media whose analytics tool, BytesView (Algodom Media, 2020), supports airline and airport operations, and the aviation research and development company Mosaic ATM (2004). On the other hand, some products are only intended for a particular aviation application. For instance, several products are built to leverage historical maintenance records and logbook data, gain valuable insights, and boost aircraft maintenance, repair, and overhaul (MRO) processes. Examples of such products include DeepNLP (SparkCognition, 2018), Avilytics (EXSYN Aviation Solutions, 2020), LexX Air (LexX Technologies, 2018), and ILARA (Church, 2021) developed by the U.S. Army Engineer Research and Development Center, Information Technology Laboratory (ERDC-ITL). Other products focus on the application of NLP in ATC; from transcribing the communicated aviation audio, which is one of the functionalities of Stratus Insight (Appareo, 2020), to assisting the aircraft crew through active interactions in natural language, as carried out by Smart Librarian (Arnold, 2020) from Airbus and the project VOICI (Clean Sky 2, 2020). Other companies devote their NLP products to improving the interactions with and support provided to customers in the airline industry or to better quantifying customer experiences, like Lexalytics and its Airlines Industry Pack (Amherst, 2015).

For details about the area of application in the aviation industry that is targeted by each product and the underlying NLP tasks it performs, see Appendix.

Discussion

While NLP is expanding into the aviation domain, its continued advancement is considerably hindered by challenges. Two of these challenges are the domain's inherent complexity (Bhatia & Pinto, 2021) and its use of technical language that is characterized by a heavy reliance on domain-specific vocabulary and abbreviations (Tulechki, 2015). One consequence is that the performance of state-of-the-art NLP models trained on standard corpora is immensely degraded upon their application to such a specific domain (Brundage et al., 2021; Dima et al., 2021). For that reason, there is a need for extensive annotated domain-specific corpora on which NLP models can train (Dima et al., 2021), or pre-trained language models can be further fine-tuned (Bhatia & Pinto, 2021). Although there have been some recent efforts to put together relevant corpora, like in the work of Akhbardeh et al. (2020), they are limited.

Since domain-specific terminology is lacking in available knowledge bases, Bhatia & Pinto (2021) and Abdullah et al. (2017) suggest the development of aviation-focused knowledge bases that are more suited for usage in such technical applications. Furthermore, research has been directed toward tailoring language processing tools to satisfy the needs of technical domains through what is referred to as technical language processing (TLP) (Brundage et al., 2021; Dima et al., 2021; Nandyala et al., 2021). More specifically, TLP is a human-in-the-loop workflow that iteratively improves resources, such as data representations and agreed-upon entity sets and hierarchies used as annotations, in an attempt to address the challenges introduced

by the technical domains (Brundage et al., 2021). Hence, industrial leaders, along with domain experts and researchers, ought to unite to make TLP a reality (Brundage et al., 2021).

It is suggested that aviation domain experts should team up with analysts and researchers to put together aviation-specific corpora and knowledge bases, as well as develop appropriate TLP tools. A multi-disciplinary approach is recommended due to the extensive knowledge in both aviation and NLP. Together, by combining individual strengths, future efforts can lead to new or improved domain-focused NLP applications addressing challenges in aviation safety.

Conclusion

Considering the expansion of artificial intelligence into almost every facet of our lives, it only makes sense that NLP is carving its way into the aviation domain. Current research shows a benefit in classifying safety reports and, in turn, allowing for the discovery of possible trends and potential threats to aviation safety. In aviation maintenance, NLP has been used not only in the analyses of maintenance logbooks to predict foreseeable component failures but also in the assistance of MRO technicians with access to technical sources. In air traffic control, NLP has been mainly leveraged to detect or reduce communication errors as well as clarify verbal messages exchanged with pilots. NLP software that automates text and speech analyses have been growing in number and is increasingly used in the aviation industry. More specifically, NLP software has been utilized in the areas of aviation safety report analyses, maintenance operations, air traffic control, and customer interactions.

Despite the applications discussed in this paper, the full potential of NLP is not even close to being fulfilled in the aviation domain. Owing to the technical and domain-specific challenges that researchers and domain experts need to tackle, NLP still has a long way to go in aviation research. There are also multiple avenues for expansion of NLP employment in the aviation industry, especially when practitioners, notably in general aviation maintenance, are using primarily paper and pen or saved template documents. At the same time, large airlines and companies with significant resources are developing specialized artificial intelligence software solutions that improve safety and forecasting. With the cost of developing such tools continuously going down, the expansion of NLP software such that it reaches smaller operators in the aviation industry is possible and is currently a work in progress.

This paper can serve as a starting point for future research in NLP aviation applications. By tailoring existing NLP tools to the technical aviation domain, there may be potential ways to improve the existing applications or expand them into other aviation areas such as air traffic management, communication between pilots and technicians, and maintenance activities.

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Appendix

NLP Software Products in the Aviation Industry

Product (Institution)	Product Released (Institution Founded)	Application Area(s) in Aviation				Underlying NLP Task(s)								
		Safety Reports	Maintenance, Repair & Overhaul	Air Traffic Control	Customer Interactions	Natural Language Understanding	Natural Language Generation	Text Classification	Topic Modeling	Information Retrieval	Semantic Similarity Assessment	Document Summarization	Speech Recognition	Machine Translation
IBM Watson (IBM)	2010 (1911)		x	x	x	x	x	x	x	x	x	x	x	x
(Mosaic ATM) ^a	(2004)	x	x		x	x	x	x	x	x			x	
ILARA (ERDC – ITL)	2021 (1998)		x					x						
Stratus Insight (Appareo)	2020 (2003)			x		x							x	
VOICI (Clean Sky 2)	2020 (2014)			x		x							x	
DeepNLP (SparkCognition)	2018 (2013)		x			x		x		x				
Avilytics (EXSYN Aviation Solutions)	2020 (2013)		x					x						
Airlines Industry Pack (Lexalytics)	2015 (2003)				x			x				x		
Smart Librarian (Airbus)	2020 (1970)			x		x		x		x			x	
BytesView, Airline & Airport operations (Algodom Media)	2020 (2019)	x	x	x	x			x	x	x	x			
LexX Air (LexX Technologies)	2018 (2012)		x			x				x				