Embeddings for the Identification of Aircraft Faults (MERIT)

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***Abstract*—Vector representation concept proves its success in solving many real-world problems from a variety of applications. In this paper, we built a novel vector representation model for avionics system for two types of fault messages called *MERIT*. This new model aims to identify the relationship between the flight deck effects (FDEs) and the maintenance messages (MMSGs) through calculating the embedding co-occurrence matrix between them within a predefined flight leg window. The a vector space embeddings representation of *MERIT* is able to differentiate between the strong and weak relationship between messages. Moreover, we benefit from the negative sampling method to incorporate the weak relationship between the FDEs and MMSGs from different subsystems (chapters) in assessing this relationship precisely. We called the developed *MERIT* with specialized negative sampling approach *subsystem-wise MERIT*. Both developed models can be used as descriptive and predictive tasks based on the flight leg window used (one and three, respectively). The main advantage of the proposed latent aircraft system model (*MERIT*) is that it needs to be trained only once and can be easily queried using any similarity measurements between the embedding vectors, which means it is more feasible and computationally efficient than traditional machine learning algorithm, where it necessitates building a different model each time for every target FDE. We tested both models on a real Boeing dataset and the experimental results demonstrate the effectiveness of the proposed model in exhibiting the embedded relationships between fault messages and extracting the most relevant predictors.**[1]

I. Introduction

Inspired by the success of existing unsupervised machine learning techniques in the natural language processing (NLP) discipline, we have adapted the *Word2Vec* model to the aviation discipline. Our goal is to advance understanding of avionics systems and more specifically to identify the embedded structure of aircraft faults. Applying traditional machine learning models, like logistic regression (LR), require that we build a different model for each target Flight Deck Effect(FDE), which is not feasible when the number of FDE's is large. However, using the *Word2Vec* model we require one model which provides sufficient flexibility to query and identify correlations between $FDEs$ and $MMSGs$. We refer to our model as $MERIT$ (eMbEddings foR the idEntification of aIrcraft faulTs model).

Prognostics and health management (PHM) is a field of study, which focuses on enhancing the availability and reliability of a device. More specifically, prognostic assesses the degradation of a device through comparing the expected value of monitored parameters under normal conditions with the device's actual parameters. This will yield a warning of an impending failure in early stages of operation and helps with planning for taking a corrective action before failure.

In this paper we focus on two types of fault messages. The first one is called maintenance messages ($MMSGs$). It tells the aircraft ground engineers parts which maybe have malfunctioned (*door area heater does not follow command on, or off*). These kind of faults have a low priority because they are generated at an early stage of parts degradation process. The second type of fault is called the flight deck effects ($FDEs$) and it informs the flight crew that the aircraft has a serious problem. This type of faults is considered a high priority and the underlying cause must be identified and rectified before the aircraft is allowed to fly again.

An aircraft is composed of different subsystems, called chapters. Example subsystems include *landing gear* and *flight controls*. Each generated $MMSG$, or FDE fault belongs to a specific subsystem, as it appears by a pair of code, which carries the subsystem number, and a brief description of the fault, as defined by engineers. Fig. 1, depicts a schematic diagram of three different subsystems in an aircraft An aircraft is designed in a way such that $MMSGs$ and $FDEs$ faults within a subsystem are more correlated than those that reside

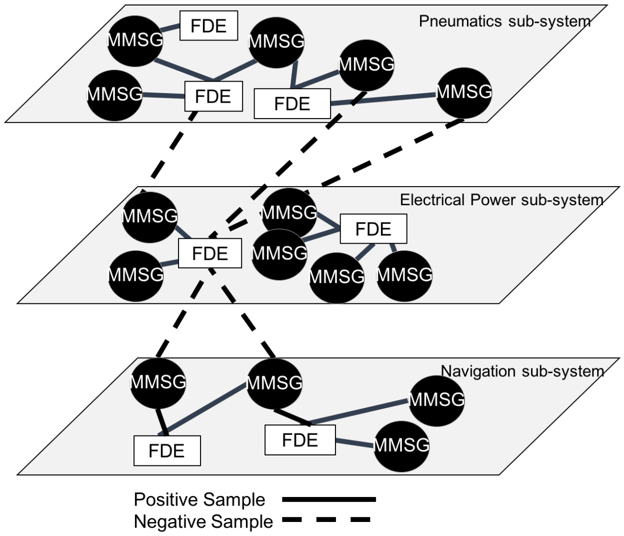


Fig. 1: Schematic diagram of three different subsystems from the Boeing avionics system.

in different subsystems.

In the *Word2Vec* model, the objective is to compute conditional probabilities of the form $P(w|c)$, where w is a *word* and c is the *context*, or $P(c|w)$. In the analysis of text, the context (c) is often the set of words surrounding w. In our proposed framework, the *MERIT* model, the words can be $FDEs$ and the context can be $MMSGs$, or vice-versa. The analogue of a text document will be one or several flight legs.

The contributions of this paper can be summarized as follows:

1) We introduce a model for embedding aircraft faults in a high-dimensional vector space to identify correlations between faults. Our system is called *MERIT*.
2) We can use MERIT to build a model for fault prediction. Unlike standard classification, MERIT provides a unified way to query faults and determined correlations between them.
3) Experiments on real data sets shows that the predictions obtained from MERIT are accurate and consistent with the expectations of domain engineers.

II. Related Work

As best of our knowledge, there is no previous work that has been done on distributional embeddings of $MMSGs$ and $FDEs$ faults, which may due to the scarceness of accessible avionics data sets. Therefore, our focus in this section will be on two aspects: (1) How the vector representation concept was exploited in other different applications to unravel the embedding structure of the given data in a specified discipline, especially in the Natural Language Processing (NLP) discipline where this technique was discovered. (2) Review previous related work, which tackles the problem from different perspectives.

This emerged field of research was inspired by the work of Mikolov and his colleagues [1], when they built novel architecture models from a collection of word vectors and gave it a general name *Word2Vec*. The designed architectures were based on the skip-gram (SG) model and the continuous-bag-of-words (CBOW) model to learn the continuous word embeddings from a huge repository of data. The main advantage of these models is their ability to accurately represent the syntactic and semantic meanings in different space windows without considering the order of the words. Their results beat all previous neural network (NN) models with less computational cost. Furthermore, these models possess an interesting point where the constructed vectors hold semantic relations. For example, suppose we aim to find the semantic relationship between a country and its capital. Given the vector representations of “England”, “London”, and “Spain”. Then, the vector embeddings of these words are algebraically related as follows:

$$v(\text{“England”}) + v(\text{“London”}) - v(\text{“Spain”} \approx v(\text{“Madrid”})$$

The same group extended their previous work, [1], to leverage the accuracy of vector representations and to accelerate the training speed by presenting different extensions of the skip-gram model, [2]. More importantly, they introduced the idea of negative sampling to their old model, which allows this new model to recognize idiomatic phrases. [3] Argued that even [2] advanced the negative sampling method to efficiently adapt word embeddings. Yet, it is not optimizing the same objective function. [4] explicated, analyzed, and compared to the negative sampling technique [2] and the noise contrastive estimation method [5], [6]. It proves that negative sampling works better for binary classification models for learning word vectors. [7] Provided a detailed explanation and equation derivation of the skip-gram model as well as the negative sampling technique.

While the *Word2Vec* model was introduced in the NLP community, it was exploited in many different domains. For example, one application where the vector representation technique was exploited is the bioinformatics discipline. Asgari and Mofrad [8] were pioneered in applying distributed vector representation to the biological sequence by introducing a new model named bio-vectors, or *BioVec*, which can represent both the proteins, also called amino-acid, and gene sequences. Their main aim were to find a distinguishable patterns from the biological sequences and facilitate interpreting the biochemical and biophysical meanings. They designed their model architectures to represent protein sequences *ProtVec* and gene sequences *GeneVec*, and used skip-gram model to train both types of sequences. The analogy of this structured models and the originated work, *Word2Vec*, is that each biological sequence deals with it as a sentence and every k-mers, which is all possible sub-sequences that can be extracted from the biological sequence with length k, as a word. In addition, the suggested models considered to include negative examples to generalize their models.

Previous work, which tackles the problem of aircraft messages faults are limited. Chérière [9], suggested a novel aircraft preventive diagnosis for airlines using failure conditions

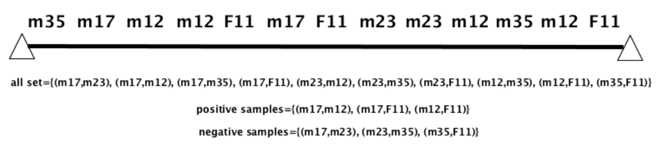


Fig. 2: An example of flight leg fault messages.

graphs. The proposed method was tested on the landing gear system of an Airbus fleet. The method introduces customized measurements such as the remaining distance. These measurements were used to get precise diagnosis and identify serious upcoming dispatch conditions. However, the proposed method is more deductive than inductive. Tsui and his colleagues, [10], present recent approaches for prognostics and health management (PHM) settings with fault diagnosis on gear crack expansion. IN addition, it predicts the remaining useful life (RUL) of rotational bearings and lithium-ion batteries applications. In a more recent work, Vogl et al., [11], carry out a risk analysis of production systems performance based on diagnostics and forecasting for maintenance of production systems.

III. Formulation of MERIT

For each flight leg, the Boeing AHM platform receives and displays many uncorrelated MMSGs from different subsystems over time before an FDE appears, as illustrated in Figure (2), informing for a failure, which may cause a catastrophic effect on the flight safety. This FDE belongs to a specific subsystem, e.g. pneumatics. Our aim is to exploit the vector representation approach to extract the most related MMSGs from a large amount of uncorrelated MMSGs. In doing so, as an analogy to the *Word2Vec* model, we dealt with an FDE as a word w, a MMSG as a context c, and the flight leg as a text corpus. Therefore, our $MERIT$ algorithm can be formulated as:

- **Given**: Flight leg dataset [2] in terms of MMSGs and FDEs, which appear in every flight leg.
- **Objective**: Build a model, which can be utilized predicting the target FDE from MMSGs.
- **Constraints**: For a given flight leg, MMSGs and FDEs from many subsystems usually appear during the same time period. Therefore, the prediction of the target FDE must depend on "true", from an engineering perspective, and not false correlation.

Let M be the set of all MMSGs and F be the set of all FDEs. We define a co-occurrence matrix flight leg (FL) of dimensionality $|F| \times |M|$ as follows:

$$FL(i,j) = \#(\text{flight legs where } f_i \text{ and } m_j \text{ co-occur})$$

[2]The dataset was collected from a fleet of Boeing 777 aircrafts comprising in total 63,356 flight legs.

		Subsystem$_1$		Subsystem$_2$	
		m_1	m_2	m_3	m_4
Subsystem$_1$	f_1	2	1	1	0
	f_2	1	1	0	0
Subsystem$_2$	f_3	1	0	1	0

TABLE I: Example of co-occurrence matrix with color coded sampling areas for V-$MERIT$. Green: positive sample and orange: negative sample.

		Subsystem$_1$		Subsystem$_2$	
		m_1	m_2	m_3	m_4
Subsystem$_1$	f_1	2	1	1	0
	f_2	1	1	0	0
Subsystem$_2$	f_3	1	0	1	0

TABLE II: Example of co-occurrence matrix with color coded sampling areas for SW-$MERIT$. Green: positive sample and orange: negative sample. Red: not considered as positive sample and white: not considered as negative sample.

Example: Suppose $M = \{m_1, m_2, m_3, m_4\}$ and $F = \{f_1, f_2, f_3\}$ be the set of all MMSGs and FDEs, respectively. Furthermore, assume that there are two subsystems, where $Subsystem_1$ consists of $\{f_1, f_2, m_1, m_2\}$ and $Subsystem_2$ consists of $\{f_3, m_3, m_4\}$. Then, we constructed the co-occurrence matrix as shown in Tables I for vanilla $MERIT$ and II subsystem-wise $MERIT$.

Similar to *Word2Vec*, the objective in $MERIT$ is to create an embedding, which will map each MMSG and FDE into a vector space with the property that maintenance messages and flight deck effects that tend to co-occur are mapped close to each other in the embedding space. Similarly, we want to encourage MMSGs and FDEs that do not co-occur in flight legs to be faraway from each other in the embedding space.

We used the skip-gram model as the core model to build the $MERIT$. Let f be an FDE and m a MMSG, the conditional probabilities $p(f|m)$, and given a flight legs of fault messages, the goal is to set the parameters θ of $p(f|m;\theta)$ so as to maximize the fault message pairs probability:

$$\arg\max_{\theta} \prod_{m \in FL} \left[\prod_{f \in C(m)} p(f|m;\theta) \right] \tag{1}$$

In the previous equation (1), $C(m)$ is the set of contexts of MMSG m. Alternatively, the objective function can be written as:

$$\arg\max_{\theta} \prod_{(f,m) \in \mathcal{F}} p(f|m;\theta) \tag{2}$$

where $\mathcal{F}$ is a collection over all fault message pairs, i.e. FDE-MMSG pairs, appearing in flight legs. We will denote the embedding of each message x as $v_x \in \mathbf{R}^d$, where d is the dimensionality of embedding space. The parameter θ corresponds to the set of all embedding vectors. Now,

Algorithm 1 SUBSYSTEM-WISE NEGATIVE SAMPLING

```
train_skipgram_pair(MMSG,FDE,m)
{
/* Use this MMSG (positive sample) plus
m other random MMSGs not from this
subsystem (negative samples) */
while ||negatives||< m do
  /* Randomly pick a MMSG from the n
  MMSGs in the flight legs accordingly
  to their frequencies */
  negM = flightlegs.MMSGOccurrence(random(0,n))
  if subsystem(negM) = subsystem(FDE) then
    continue
  else
    negatives.add(negM)
  end if
end while
}
```

$$P(f|m;\theta) = \frac{p(f,m)}{p(m)} = \frac{e^{v_f \cdot v_m}}{\sum_{f' \in F} e^{v_{f'} \cdot v_m}}$$

Hence, the number of unknowns are $(|F| + |M|) \times d$, i.e. an embedding for each FDE and MMSG. Now, taking logs of the objective function in the aforementioned equation, we get:

$$\arg\max_{\theta} \sum_{(f,m)\in\mathcal{F}} \log p(f|m) \equiv \tag{3}$$

$$\arg\max_{\theta} \sum_{(f,m)\in\mathcal{F}} (\log e^{v_f \cdot v_m}) - \log \sum_{f' \in F} e^{v_{f'} \cdot v_m} \tag{4}$$

The above optimization is the standard word2vec formulation. The reason the optimization problem is hard to solve is due to the second term, where the summation is taken over all FDEs. One popular approach that has been proposed to approximately solve the optimization is to use the concept of negative sampling. As we show next, we will incorporate subsystem information in the negative sampling process. In [3] it is shown that the use of negative sampling is equivalent to optimizing the following objective function:

$$\arg\max_{\theta} \sum_{(f,w)\in\mathcal{F}} \log \sigma(v_f \cdot v_w) + \sum_{(f,w)\in\mathcal{F}'} \log \sigma(-v_f \cdot v_w) \tag{5}$$

where $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid function and $\mathcal{F}'$ is the set of negative samples or pairs of (f, w) which have a low probability of occurring in the training set.

IV. $MERIT$ NEGATIVE SAMPLING

Negative sampling is an efficient approach to estimate the parameters of the *Word2Vec* model by drawing only a subset of all the possible contexts [2]. In the *Word2Vec* model every word is a context. For $MERIT$, we use (f, m) pairs. Note that the goal of negative sampling is to generate pairs of (f, m_j), which are unlikely to appear together. For each pair of (f, m) that occur together in the dataset, k negative samples $(f, m_1), ..., (f, m_k)$ are randomly drawn from M and F according to their frequency distribution.

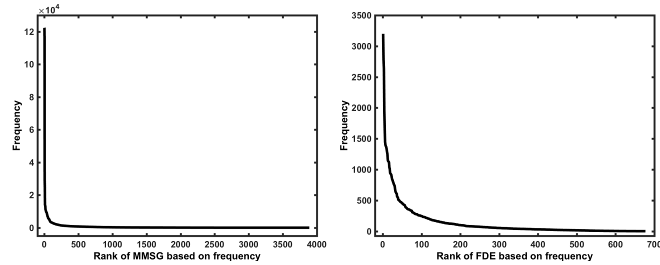


Fig. 3: Frequency of MMSGs and FDEs.

Intuitively, by enforcing negative sampling from different subsystems, MMSGs from a different subsystem than the FDE's are penalized, in the sense that their embedding vector representations will be more dissimilar from the embedding vector representation of the FDE. Conversely, the MMSGs are in the same subsystem of the FDE will have a vector representation more similar to the FDE's vector representation, because they are never taken as negative samples for FDEs of the same subsystem. **Algorithm (1)** explains the negative sampling function for the skip-gram model.

V. EXPERIMENTS AND RESULTS

We evaluate the $MERIT$ model performance on the data set, which was recorded by the Boeing fleet of aircrafts.

A. Data Set

The data set used in this paper was taken from the log files recorded during flight legs. This data set was recorded from 63,356 flight legs from 42 different airplanes. Out of these flight legs, there are 22,433 flight legs, which recorded FDEs along with MMSGs, while the rest of the flight legs (40,923) contain only MMSGs. The data set contains a total of 450,209 MMSGs with 3,889 unique MMSGs and 95,732 FDEs with 677 unique FDEs. The frequency of these FDEs ranges between 1 - $\sim$3,200 times and the frequency of total FDEs per subsystem ranges between 1 - $\sim$24,000 times. Similarly, the frequency of the recorded MMSGs ranges between 1 - $\sim 120\times10^4$ times. Figure 3 exhibits the frequency of both MMSGs and FDEs.

The collected data set represents 30 subsystems out of the total 80 subsystems. Each subsystem is composed of a collection of units (modules). The number of these units varies from one subsystem to another, where it ranges between 1 and 14 units. The total number of these units is 83.

B. Types of Experiments and Data Pre-Processing

In this study, we have carried out two types of experiments based on the way of extracting the features of the data set, which can be summarized as follows:

1) Descriptive (one flight leg): we consider each flight leg fault messages as one sentence, like vanilla $MERIT$. The sentence includes all MMSGs and FDEs of the chosen flight leg.
2) Predictive (three flight legs): the featured dataset, which represents the prediction task was built as follows:
   - Let F = [set of all unique FDEs from the flight leg(x+3)].
   - Let M = [set of all unique MMSGs from the previous flight legs: leg(x), leg(x+1), leg(x+2)]
   - For each target FDE in the F, we built a sentence as [f, M].

C. Experimental setup and evaluation

For both types of designed experiments, we use the vanilla *W*ord2Vec model (applied to the Boeing fleet of aircrafts dataset) and the subsystem-wise model. We refer to the vanilla model and subsystem-wise models as V-$MERIT$ and SW-$MERIT$, respectively. The settings for both models can be summerized as follows:

1) Vanilla $MERIT$ model, which has the following setup:
   - Skip-gram model with a window length = 500.
   - Embedding features = 300.
   - Negative sampling = 5.
   - Random reduced window.
2) Subsystem-wise $MERIT$ model, which has the following setup:
   - Skip-gram model with a window length = 500.
   - Embedding features = 300.
   - Negative sampling = 5 and SHOULD be from subsystem different from the target FDE.
   - No reduced window.
   - Positive sampling: pairs (M1, M2) both SHOULD belong to the same subsystem as the target FDE.

D. Results: description experiments and semantic preservation

The evaluation of the *W*ord2Vec model is a challenging task. Therefore, for description experiments, we depend on the novel property "semantic preservation" of the *W*ord2Vec model by observing the algebraic relationships in the embedding space:

$$AR_1: \text{FDE}_i + \text{FDE}_j - \text{MMSG}_j \approx \text{MMSG}_i$$

$$AR_2: \text{MMSG}_i + \text{MMSG}_j - \text{FDE}_j \approx \text{FDE}_i$$

Here, i and j represent subsystems. We proceed this experiment as follows: For each triple (f_i, f_j, m_j), we compute the vector representation of x as: $x \equiv v(f_i) + v(f_j) - v(m_j)$. Then, we obtain the nearest $MMSG$ vector representation to x in the embedding space. If the resultant vector representation belongs to the same subsystem as i, then we consider this algebraic relationship (AR_1) as a success, as it indicates that both fault messages are semantically related through subsystem information. Similarly, we evaluate the second algebraic relationship AR_2 (m_i, m_j, f_j).

$v(f_i) + v(f_j) - v(m_j) \simeq v(m_i)$
v("32904092") + v("23042949") - v("23-82074") $\simeq$ v("32-94228")
v("27006860") + v("32491565") - v("32-47230") $\simeq$ v("27-08113")
v("34342027") + v("78177761") - v("34-35480") $\simeq$ v("78-12350")
v("32430068") + v("23269848") - v("32-44210") $\simeq$ v("23-28408")
v("32590288") + v("23160444") - v("23-18482") $\simeq$ v("32-59533")

TABLE III: WS-$MERIT$ examples for validating algebraic relationship AR_1.

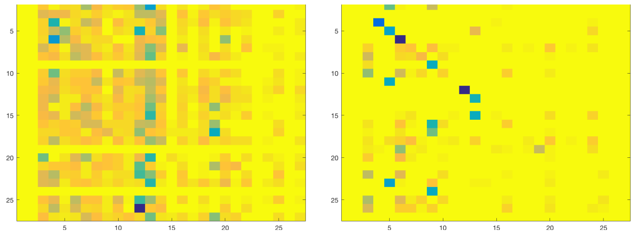
$v(m_i) + v(m_j) - v(f_j) \simeq v(f_i)$
v("28-97432") + v("32-02368") - v("32070948") $\simeq$ v("28921409")
v("23-36953") + v("52-65977") - v("52615696") $\simeq$ v("23384752")
v("23-89146") + v("32-33748") - v("32374071") $\simeq$ v("23812005")
v("34-56438") + v("23-73528") - v("23790642") $\simeq$ v("34551608")
v("32-07304") + v("24-85942") - v("24854730") $\simeq$ v("32081629")

TABLE IV: WS-$MERIT$ examples for validating algebraic relationship AR_2.

Table III shows examples for operation AR_1 and Table IV for operation AR_2 across different subsystems. In each case, we were able to recover the fault message from the correct subsystem.

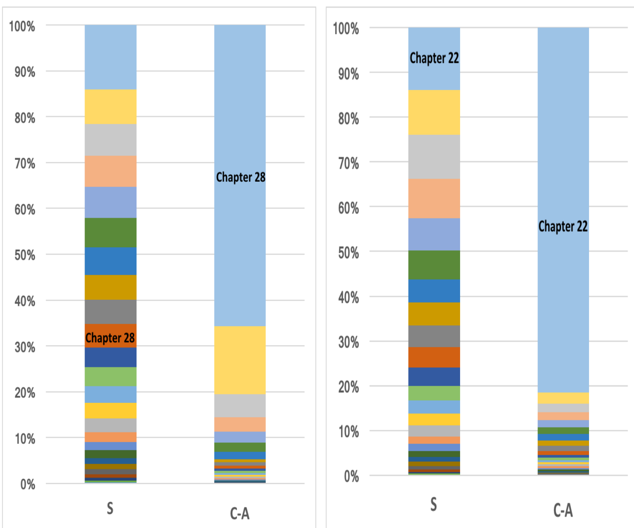
Figure 4(a) shows the complete analysis for all the subsystems for V-$MERIT$ and Figure 4(b) for SW-$MERIT$. Both rows and columns of the images are indexed by subsystems. Since the diagonals of the matrix in Figure 4(b) dominate for many subsystems, it indicates that SW-$MERIT$ is superior to V-$MERIT$ in recovering semantic relationships between faults based on algebraic relationship AR_1.

Moreover, we performed a more generalization experiments for D-EXP and algebraic operations. Figure 5 shows two illustrating examples of general algebraic operation v('target FDE') + v('FDE$_m$') - v('MMSG$_m$') = ?. In this operation, we only fix the target FDE and the remaining objects are randomly chosen. The only constraint is that the selected FDE and MMSG should belong to the same subsystem, i.e. m. Figure 5 (a) shows the predicted percentage of MMSGs, which belong to subsystem 28, as the target FDE. For the V-$MERIT$ model (left bar), it predicts $<$10%, while the SW-$MERIT$ model (right bar) is able to predict $>$65% MMSGs that belong to subsystem 28. Similarly, figure 5 (b) depicts another example when the target FDE belongs to subsystem 22. In this case, the V-$MERIT$ and SW-$MERIT$ models predict $\sim$15% and $>$80% MMSGs from subsystem 22, respectively.



(a) (b)

Fig. 4: Heat map of subsystem to subsystem relationship for V-$MERIT$ (a) and SW-$MERIT$ (b) for algebraic relationship AR_1. The dominating diagonals of the right figure shows that SW-$MERIT$ is more accurate in recovering semantic relationships than V-$MERIT$.

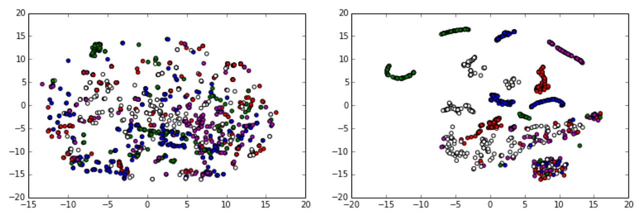


(a) 28921409+FDE$_i$-MMSG$_i$=? (b) 22103200+FDE$_l$-MMSG$_l$=?

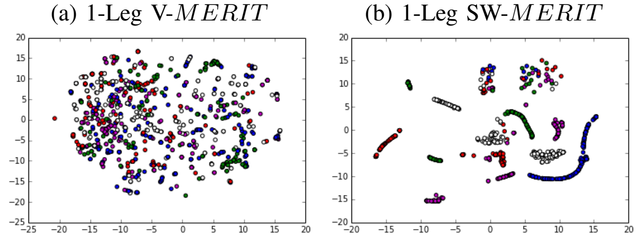
Fig. 5: General examples of an arithmetic operations to predict the MMSGs from the same subsystem as the target FDE for the vanilla and subsystem-wise $MERIT$ models. Here, i and l were chosen randomly.

Subsystem #	Total # of messages		Avr. Comp. Ratio
	S	CA	S vs. CA
12	8	8	224.3 times
21	272	221	5.3 times
24	313	130	4.1 times
30	66	60	2.8 times
73	221	151	8.6 times

TABLE V: Average compactness ratio (the ratio of average distances between all fault messages) within a subsystem in the vanilla and subsystem-wise $MERIT$ models for three flight legs window.



(a) 1-Leg V-$MERIT$ (b) 1-Leg SW-$MERIT$



(c) 3-Leg V-$MERIT$ (d) 3-Leg SW-$MERIT$

Fig. 6: A two-dimensional visualization, using Dimensionality reduction, of the embedding space using both V-$MERIT$ andSW-$MERIT$. The color codes represent subsystems: '21':white, '22':green, '28':red, '34':blue, '32':magenta. The plots show that the SW-$MERIT$ provides superior clustering quality compared to V-$MERIT$.

E. Results: Original Embedding Space

Table V illustrates the average compactness ratio, which is the ratio of average distances between all fault messages in a specific subsystem. We randomly choose five different subsystems. The first row shows that subsystem 12 has 8 fault messages in total for both V and SW $MERIT$ models. However, there is a huge difference between both models, where the average distance calculated using the V-$MERIT$ model is 224.3 times larger than the average distance calculated using the SW-$MERIT$ model. Similar observation can be seen for other subsystems.

F. Results: Dimensionality Reduction of Embedding Space

Another perspective on the clustering quality of V-$MERIT$ and SW-$MERIT$ is provided by carrying out a dimensionality reduction of the embedding space. The results presented in Figure 6 illustrate visualizations for both types of data, that is data corresponding to co-occurrence matrices created both (a, b) on one flight leg and (c, d) on three flight legs.

G. Results: Interpretation of the Embedding Space

In Table VI, we show that the dimensions of the embedding space can be interpreted as representing subsystems. We have chosen four dimensions at random and ranked all faults (both MMSGs and FDEs) by their coordinate values. This was carried out on both the V-$MERIT$ and SW-$MERIT$. It is clear that SW-$MERIT$ is much better in associating dimensions with subsystems. For example, the top 35 ranked faults of embedding dimension 5 (for three leg data) are associated with subsystem 34.

H. Results: Prediction Experiments

The accuracy of predictions is one of our goals. Meanwhile, in working with the subject matter experts we learned that there are cases when prediction rules (or prediction models)

Window size		One flight leg		Three flight legs	
Model	Rank	1	20	5	267
V-$MERIT$	1	36504838	27-61115	31-55370	23-31871
	2	34844049	28-47893	26-95706	26-17068
	3	31-04909	28-92091	31-82888	32-80088
	4	31-18795	28-27340	26-59794	32-76884
	5	31-89550	28-98500	24-20273	24-88854
	6	32651785	23-21594	24-54010	41-89259
	7	31-27500	23-85682	31-95004	34-96331
	8	30-15186	28-09845	24-36144	26-75152
	9	34669103	36-62847	21-24135	26-55078
	10	31-53234	27-35885	27-04655	24-41597
		...	...	...	...
	31	36-72056	28-39753	49-28780	22-64617
	32	31-99940	31-29184	31-99719	34-24103
	33	27-19571	27-56147	23-43512	28-13864
	34	31-54302	28-42444	31-79937	21-38172
	35	28758598	27-29886	34-55775	34-88078
SW-$MERIT$	1	31-92501	34619741	34-64320	22964135
	2	31-13605	34876093	34-92906	22280530
	3	31-48853	34395433	34-24912	22-10526
	4	31-06387	34337981	34-05685	22-14268
	5	31-30954	34-91838	34-58979	22-36295
	6	31-17322	34633014	34-26681	22-42553
	7	32387343	34139081	34-52721	22-13841
	8	31-59130	34305937	34-26272	22-23124
	9	32074993	34-56994	34-56589	22-41889
	10	31-28154	34-21341	34-67783	22-11964
		...	...	...	...
	31	31-08372	34235213	34-28920	22-26753
	32	31-16405	34761190	34-49738	22-34817
	33	31-74192	34-84614	34-81782	22-46825
	34	31-00232	34-73933	34-62279	22-90106
	35	31-77801	34566334	34-46162	22-96623

TABLE VI: Top ranked MMSGs and FDEs in two different coordinates randomly selected from the 300 dimensional embedding space in the vanilla (top rows) and subsystem-wise (bottom rows) $MERIT$ models for one and three flight leg messages.

may not make physical, technical or logical sense, and those rules had to be eliminated from the final model. An aircraft is an engineered system where internal subsystems obey the laws of mechanics. Our interaction with aerospace engineers has led to the following conclusion: while it is possible that occasionally a MMSG from one subsystem will cause an FDE in another subsystem, in most cases the dominating predictive variables (for an FDE) should be from the same subsystem.

The three leg data, where we use MMSGs from three previous legs to predict an FDE was designed to test the particular hypothesis that the most important predictors of an FDE are within the subsystems. The results are shown in Table VII. Both the V-$MERIT$ and the SW-$MERIT$ models are superior to logistic regression with both $L1$ and $L2$ regularizers. Furthermore, note that the logistic regression models were built one FDE at a time, while $MERIT$ models were built ALL AT ONCE to predict all the FDEs. Thus, the $MERIT$ models are easier to use in practice and more relevant for the integration into a predictive maintenance tool. Moreover, they are able to handle more elegantly the skewed input data distributions.

VI. Conclusion

In this paper, we proposed a new $MERIT$ model, which is a distributed representation paradigm for aircraft faults. We illustrated the benefits of our framework by utilizing the learned embeddings for describing the MMSG-FDE relationship and predicting a target FDE fault. The contribution of this work can be summarized in these points: (1)- Pioneering in deploying the *Word2Vec* model into an avionics discipline and named this novel model $MERIT$. (2)- Identifying the embedded structure of the Boeing aircraft aviation system through finding the correlation between the FDEs and MMSGs, which belong to the same subsystem. (3)- Exploiting the existing sequential information regarding the MMSGs from the prior flight legs to predict the top predictors MMSGs of a specific FDE. (4)- The $MERIT$ model outperform logistic regression algorithm and computationally faster because it needs to be train once. (5)- We developed a specialized negative sampling method called *subsystem-wise negative sampling* to advance understanding the relationship between MMSGs and FDEs and leverage the prediction accuracy.

The future work can be moved in many directions: for example, we take one step further in depth by predicting the associated component within a subsystem for the target FDE, instead of predicting the MMSG from the same subsystem.

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TABLE VII: Top-5 MMSGs predictors of the target FDE using logistic regression and $MERIT$ models for three leg data. Recall we use three previous flight legs to predict the FDE in the current flight leg.

MODEL	WINDOW SIZE	FDE	SUBSYSTEM #	TOP-5 MMSGS
LOGISTIC REGRESSION L1	-	21833368	21	24-58024 28-62555 75-02076 21-56956 33-65760
		28263212	28	22-92463 26-12353 24-52683 28-58283 31-64692
LOGISTIC REGRESSION L2	-	21833368	21	24-20639 28-68301 75-25575 21-86459 33-39056
		28263212	28	28-95667 26-72573 22-07012 24-94195 31-11285
V-$MERIT$	THREE LEGS	21833368	21	21-75373 21-74305 31-04213 34-10621 21-77914
		22327300	22	32-93127 22-34784 34-53751 52-02740 34-30511
		23886774	23	23-63623 23-61228 23-67896 23-68964 23-60824
		23900047	23	23-30252 23-33716 23-37988 23-31579 73-01008
		27323255	27	27-98872 27-90327 32-58687 27-90990 27-99276
		28263212	28	28-81118 28-88595 28-84322 23-31320 58-09958
		34889366	34	34-62998 34-66202 34-65134 34-68339 34-67675
		34277939	34	34-07196 34-04251 34-05319 34-01046 34-07860
		34288620	34	34-74084 34-73016 34-72611 34-78356 34-71543
		36113673	36	74-21966 74-39865 21-17030 74-93531 31-01413
		52594333	52	52-42040 52-49112 52-49921 30-96515 52-46717
SW-$MERIT$	THREE LEGS	21833368	21	21-78577 21-76846 21-79424 21-79020 21-70475
		22327300	22	22-32022 22-37104 22-34967 22-39499 22-39240
		23886774	23	23-65096 23-61892 23-62960 23-64983 23-69256
		23900047	23	23-65388 23-67524 23-62184 23-63252 23-69920
		27323255	27	27-17986 27-13049 27-14118 27-11318 27-14781
		28263212	28	28-81669 28-82737 28-82478 28-81005 28-83805
		34889366	34	34-91687 34-91282 34-91282 34-95555 34-99568
		34277939	34	34-85278 34-83142 34-84873 34-87414 34-86346
		34288620	34	34-11981 34-14522 34-11577 34-16917 34-15590
		36113673	36	36-30544 36-30500 36-30348 36-30212 36-38280
		52594333	52	52-29735 52-24799 52-25462 52-25203 52-20931