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A FRAMEWORK FOR AUTOMATIC CAUSALITY EXTRACTION USING SEMANTIC SIMILARITY

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ABSTRACT
Textual documents are the most common way of storing and distributing information within organizations. Extracting useful information from large text collections is therefore the goal of every organization that would like to take advantage of the experience encapsulated in those texts. Entering data using a free text style is easy, as it does not require any special training. However, unstructured texts pose a major challenge for automatic extraction and retrieval systems. Generally, deep levels of text analysis using advanced and complex linguistic processing are necessary that involve computational linguistic experts and domain experts. Linguistic experts are rare in engineering organizations, which thus find it difficult to apply and exploit such advanced extraction techniques. It is therefore desirable to minimize the extensive involvement of linguist experts by learning extraction patterns automatically from example texts. In doing so, the analysis of given texts is necessary in order to identify the scope and suitable automatic methods. Focusing on causality reasoning in the field of fault diagnosis, the results of experimenting with an automatic causality extraction method using shallow linguistic processing are presented.

Keywords: automatic causality extraction, natural language processing, supervised machine learning, semantic similarity

1. INTRODUCTION
A keyword-based search is commonly used for computer-supported retrieval systems. It is proven to be efficient and useful when retrieving a list of documents whose contents are assumed to consist of similar terms to the keywords. However, keyword searching provides only limited support when locating and extracting specific piece of information rather than retrieving a whole document. Extracting specific information out of documents requires the comparison of information at a fine-grained level for which string-based indexing is not suitable. If extracted information can be structured into a database-like format, not only would this enable easier access to the documents but also provide a basis for advanced information processing. For example, new information could be discovered by relating disparate pieces of information within a single document or across documents.

An important semantic relation for such information extraction is the causality that refers to the way of knowing if one state of affairs causes another [21]. Causality helps to predict the future; achieve goals on the basis of actions; and explain why something has happened. Causality in this paper is defined as the relation between two states of affairs when the occurrence of one state of affairs, referred to as the cause, is perceived by a user as leading to the occurrence of another state of affairs, referred to as the effect. It is especially important in medicine and engineering. In medicine, it is concerned with developing treatments and drugs that can influence a cure for some disease. In engineering, fault detection and diagnosis are routine tasks and increasing interest is being devoted to developing structured approaches for identifying and resolving faults. One example area is the investigation of safety-critical events such as aviation accidents and incidents. Investigators are responsible for deriving potential contributing factors to those events and publishing the results in accident or incident reports. They examine the evidence and claims before drawing conclusions about what triggered the events and recommending suitable safety measures. This requires intensive concentration on the issues that differentiate minor causes from major ones. Often the investigators need to refer to previous reports to reuse existing findings.

Studies like [4, 10, 34] reported difficulties when accessing and extracting reusable information from aviation accident reports. One difficulty is due to the complexity entailed when tracing the evidence towards a particular conclusion, since the evidence can be distributed over many pages in a single report. Another difficulty is due to the implicitly expressed evidence such that readers are forced to infer links between the evidence and the argument. As a consequence, the readers tend to make causal inferences that were never intended by the investigators. Among other things, these difficulties undermine attempts to reuse previous findings in order to prevent reoccurrences of the events causing accidents or incidents. An automatic causality extraction tool for identifying causality sentences and extracting the descriptions of the cause and effects from the sentences would therefore be useful.

Reviews of related researches indicate that certain types of causality expressions have rather fixed linguistic patterns. Such patterns can make it easy to develop an automatic extraction rules. These rules are often based on cue phrases consisting of lexical words and syntactic constraints. This paper presents a framework for an automatic causality extraction approach using such simple linguistic patterns. In doing so, empirical analysis of texts is carried out in order to identify the types of causality expressions. Fifty aviation accident reports have been used for the analysis and it was observed that: (1) because of the importance of causality, causality expressions tend to be explicitly indicated using linguistic connectives which makes the automatic extraction using machine learning based on shallow processing more feasible; and (2) most ambiguity in extraction is due to the extraction pattern using causative verbs. To address, the semantic similarity between the descriptions of cause and effect is identified. When tested with ten new accident reports, the approach showed 72% precision with 67% recall, which is comparable to other approaches.

2. RELATED WORK

Extracting text fragments that are particularly interesting has been actively researched within Information Extraction (IE). IE is a sub-field of Natural Language Processing (NLP) aimed at extracting entities that have pre-defined types, i.e. Named Entities (NE), using shallow NLP techniques, e.g. Part-Of-Speech (POS). IE can process a large number of documents effectively. It has demonstrated a significant improvement in retrieving relevant information compared to keyword searches [9].

IE structures information into easily accessible formats by identifying NEs and the relationships between them. NEs are pre-defined lists of domain entities. Generally, NEs are proper names of organizations, persons and locations. By highlighting the extracted NEs, it helps users to visually scan a large number of documents.

Causality extraction is different from the NE identification in that it not only needs to determine whether a given sentence contains causality, but also it needs to extract a pair of cause and effect from the sentence by identifying which parts of the sentence denote the cause and the effect. In doing so, a sentence-level classification that classifies a sentence into one of a number of pre-defined sentence types is necessary. Example applications of the sentence-level classification are semantic orientations and causality extraction. Semantic orientation looks for the evaluative character of a word in order to extract opinions, feelings, and attitudes expressed in a text [32]. The orientation is classified as positive if it contains praise or recommendation. Negative orientation indicates criticism or non-recommendation. The semantic orientation does not apply to sentences that contain only facts. Wiebe and Riloff [33] proposed a classification method that classifies a sentence as subjective if the sentence expresses a positive or negative opinion, otherwise as objective. A combination of cue phrases, e.g. *excellent* or *low fees*, and linguistic features is commonly used. Those cue phrases can be created either manually or using a learning technique, e.g. PointWise Mutual Information (PMI)-IR or naive Bayesian. On average, the accuracy is observed to be around 70%.

Recently, there has been great interest in automatic causality extraction from semi-structured or unstructured texts. In early work, knowledge-based approaches using various methods to infer causality have been attempted by [11, 29]. They developed a prototype of extracting causality from short explanatory texts entered into the knowledge acquisition component of an expert system. Domain knowledge was pre-compiled to help when ambiguity existed. When tested with sample texts, the prototype was able to achieve high accuracy, but as the inferences were hard-coded, new types of texts were not easily added. Researches like [5, 6, 8, 12, 13, 26], on the other hand, have attempted to extract causality without knowledge-based inferencing.

Khoo et al. [13] constructed five extractions patterns that were strictly syntactic and thus did not rely on domain knowledge. Girju focused on the third pattern of them, i.e. NP_1 *verb* NP_2, where the verb is a synonym of *cause* or reflects a resulting effect in the NP_2. [8]. She exploited various semantic relations defined in the WordNet [22] to resolve potential ambiguity due to multiple meanings of the verb. That is, the semantic categories of NP_1 and NP_2 act as semantic constraints to test whether the verb means causality in this specific sentence. The constraints were based on the findings in [14] that the nouns representing either causes or effects are types of events, conditions, states, phenomena, or processes. As such, when the given verb is ambiguous, the semantic categories of NP_1 and NP_2 are used to identify the correct sense of the verb. For example, in the sentence of *Hitler's' invasion of Poland provoked the Second World War*, both *invasion* and *Second World War* belong to the causation sense *event* according to the WordNet, so even if the verb *provoke* is ambiguous, this sentence is detected as causality. Using the TREC-9 dataset that is a collection of news articles, a total of 300 causality sentences were detected by the system. When two human annotators were asked to rank the 300 sentences, only 151 were evaluated as referring to causation by the annotators. The accuracy of the system in comparison with the average of the two annotations was 65.6%. Such semantic constraints were also used in [6]. On the other hand, Chang et al. exploited the probability distribution of NP_1 *and* NP_2 to quantify the co-occurrence preferences of both phrases in a large corpus. This lexical pair probability was also used to detect discourse relations between two sentences [20]. Both used the Naïve Bayesian to compute the probability distribution.

Koo et al. [12] further extended their work to make use of full syntactic parse results. They manually constructed extraction patterns that specified the various ways causal relations could be explicitly expressed in sentences. Similarly, Cole et al. focused on constructing a syntactic framework from which causality could be extracted directly [6]. They were mostly concerned with one causality pattern, i.e. NP_1 verb NP_2. Pechsiri et al. [26] reported reusable extraction patterns most of which were created manually from training examples. Using various linguistic parsing patterns, and focusing on explicitly defined causal descriptions, the approaches were able to generate a number of reusable extraction patterns.

Overall, current automatic systems achieve around 60-70% accuracy. The work by Takashi et al. [31] was shown to achieve over 85% precision but the causality evaluated was only related to one linguistic pattern using subordination connectives such as *because* or *so*.

3. THE PROPOSED APPROACH

When an event occurs, it is common to observe that more than one cause contributed to the event, and rather complex relations among causes and effects took place. Often the causal descriptions are shown as a kind of causal chain. Whereas current approaches tend to focus on a single cause effect relation by isolating its association from the rest of the relations, in practice it is difficult to untangle them when understanding how and why the event was caused. In previous work, we demonstrated the usefulness of such causal chains when understanding aviation accident reports [17]. When tested with eight subjects, it was observed that the chains helped the subjects to understand better the events such that they could answer questions quickly and accurately. One shortcoming of the work was its reliance on manual annotations. That is, using the computational linguistic theory, i.e. Rhetorical Structure Theory, the sentences describing causes and effects were manually annotated. This paper aims to reduce the manual annotation by learning extraction rules from example causality expressions.

Current approaches to automatic extraction rely on experts in human-computer language or computational linguistic. For example, Koo et al. [12] have manually created 68 extraction patterns each of which consists of a causality connective used to indicate the presence of causality, and a rule specifying which parts of a sentence represent causes and effects. In engineering, it is difficult to find such experts posing a major problem of developing automatic identification. In addition, it is time-consuming and domains-specific, preventing the reuse of the extracted rules for a new domain. Since new causality expressions are constantly emerging, manually created rules quickly become obsolete. It is therefore desirable to minimize the extensive involvement of linguist experts by learning extraction patterns automatically from example texts. In addition, automatic extraction enables the mining of a large number of documents quickly and reuse in other domains.

3.1. Automatic Causality Extraction from Texts

Causality is a central element for humans to perceive and interpret the interaction between different states of affairs. This is revealed by the multitude of different forms of expression of a single causality. A common way of connecting two states of affairs is by explicitly marking them through a linguistic connective, e.g. *because*. Causality is assumed as presupposing a temporal relation, in that the cause must always precede the effect in time [21]. However, without observing the occurrence of the causal event directly, humans are able to infer the fact that there is a causal relation between states of affairs based on observations of their temporal succession. As such, for some cases, an explicit connective is not necessary. For example, the following two sentences are both causality sentences, but the second sentence describes causality without using the connective but through juxtaposition:

(1) ***Because*** *flying times and fuel records were incomplete, an accurate average fuel consumption rate for the helicopter was not possible.*

(2) *Flying times and fuel records were incomplete. An accurate average fuel consumption rate for the helicopter was not possible.*

Causal analysis requires focused and significant cognitive efforts in order to identify and interpret observed events correctly. For a complex event, there exist various explanations based on evidence related to the events. Although in current practice, it is difficult to completely automate all the causal analysis processes for inferring a link between disparate causality in a meaningful way, helping engineers with a tool to automate some of the processes would be very beneficial.

This research focuses on explicitly defined causality. That is, the automatic extraction of the second sentence above is beyond the scope of this paper. One reason is that not only it is difficult to extract implicitly implied causality automatically but also the interpretation of such expressions regarding causality can differ among engineers, such that reuse is limited.

Figure 1 shows an example of an automatic causality extraction tool. To start, the tool actively retrieves and analyses the contents of retrieved documents in order to identify sentences expressing causality. The identified sentences are further analyzed and the pairs of causes and effects are extracted from them. As shown in Figure 1, there are two effects caused by a single cause. The highlighted, *cause* and *result in*, act as linguistic connectives to explicitly indicate the existence of causality.

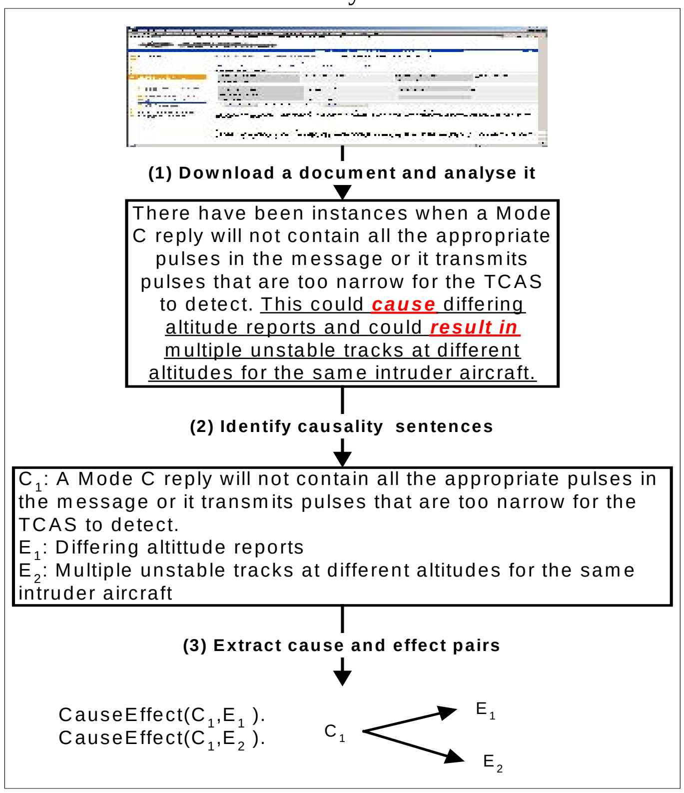

Figure 1. An example of automatic causality extraction

3.2 Dataset

This research has used 50 aviation accidents reports as a basis for domain analysis. These reports were collected for the research into the identification of design-induced errors [30] and were downloaded from the Australian Transport Safety Bureau (ATSB) database. The accidents occurred between 1994 and 2000. Each report was manually annotated and stored in XML format. A total of 3995 sentences were extracted. The dataset was initially annotated with the concepts needed for identifying human and design errors. Therefore, it is necessary to re-examine the dataset for this research.

3.3 The Proposed Framework

A framework has been developed that provides a graphical user interface for annotating examples; a learning algorithm that constructs extraction rules using the annotated examples; and a prediction function that predicts whether a new sentence contains causality using the learned rules. In contrast with other approaches, this provides extensive helps to engineers throughout the steps involved in causality identification. Using this framework, it is easier to collect annotated examples, and the annotation results can be easily verified. Figure 2 shows the framework which consists of three tasks, each of which is described in the following sections.

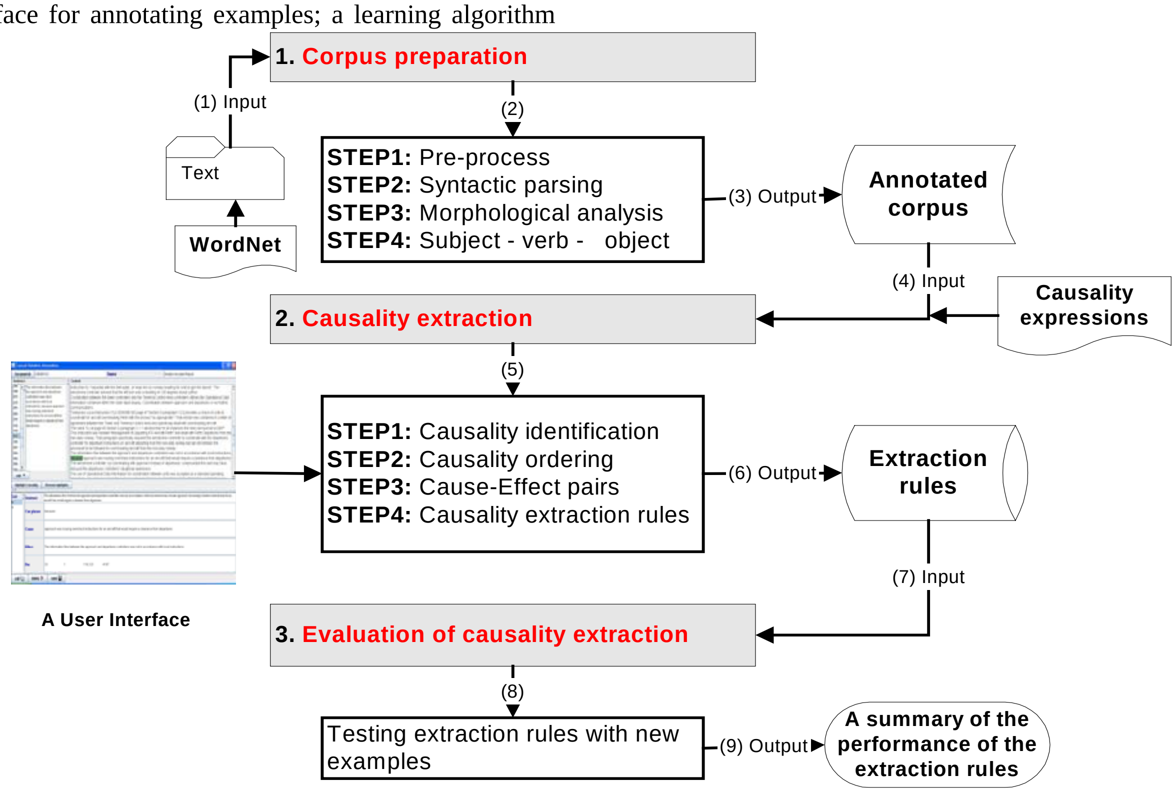

Figure 2. The proposed framework

3.3.1 Corpus preparation

This task takes an unstructured document as its input and analyses it using shallow NLP techniques. By definition, NLP is a set of computational techniques for analyzing and representing natural language documents at one or more levels of linguistic analysis for human-like language processing [2]. It is difficult to use fully-fledged NLP. This is especially true for pragmatic and discourse analysis aimed at interpreting the meanings conveyed across sentences and understanding the purposeful use of language in situations, particularly those aspects of language that require world knowledge. Researches such as [18] suggest benefits of implementing NLP at the lower levels of analysis. One advantage is that since shallow processing has been thoroughly researched, the analysis results tend to be more accurate and it is relatively easier to find reusable automatic tools. For example, a wide range of free POS tagging tools is available [35]. As such, engineers without background knowledge of computational linguistics can make use of shallow NLP techniques. In this paper, the shallow processing is implemented in four steps: (1) pre-processing; (2) syntactic parsing; (3) morphological analysis; and (4) subject-verb-object extraction.

Step 1: a document is pre-processed by: (1) decomposing it into a set of paragraphs each of which consists of sentences; (2) removing symbols, e.g. --; and (3) identifying terms.

Step 2: each sentence is then fed into the Apple Pie Parser for a syntactic parse [28]. The Apple Pie Parser uses grammar rules from the Penn Treebank [19] when determining the POS taggings and the sentence's entire grammatical structure. POS identifies not what a word is, but how it is used. It is useful to extract the meanings of words since the same word can be used as a verb or a noun in a single sentence or in different sentences. In a traditional grammar, POS classifies a word into eight categories: verb, noun, adjective, adverb, conjunctive, pronoun, preposition and interjection. The grammatical structure reveals the structural dependency between the terms such as verb phrase or indirect objects.

Step 3: each POS-tagged word is compared with WordNet definitions [22] to achieve term normalization, e.g. *caused* is converted into *cause*.

Step 4: the triple of Subject-Verb-Object (SVO) is extracted from the analyzed sentence. SVO is often referred to as predicate-arguments where predicate is a verb and arguments are subject and object. Figure 3 shows an example output of the annotation for the sentence of *The engine's loss of power was caused by the fuel exhaustion*. The meaning of POS taggings used as: (1) S: simple declarative sentence; (2) NP: noun phrase; (3) VP: verb phrase: and (4) PP: prepositional phrase. By representing the sentence in the triple format, it is easier to extract two arguments, i.e. cause and effect, for the causative verb of *cause*.

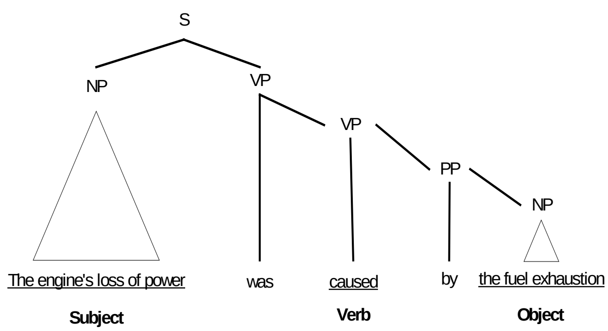

Figure 3. An example of annotated sentence

Table 1 shows most the commonly occurring verbs and nouns along with the total number of occurrences in the 50 accident reports. The total number of verbs and nouns are 6844 and 25082, respectively. The reports are documents of 2-3 pages that average around 80 sentences.

Table 1 Common verbs and nouns in the dataset

Verb	Noun
Report (46)	Pilot (125)
Use (41)	Aircraft (96)
Require (40)	Crew (81)
Provide (27)	Occurrence (74)
Issue (22)	Controller (68)
Indicate (22)	Date (50)
Operate (22)	Flight (28)
Include (21)	Operator (27)
Maintain (19)	Time (22)
Conduct (18)	Investigation (20)

3.3.2 Causality extraction

This takes a linguistically annotated sentence as an input and extracts causality as shown in Figure 1. In doing so, three tasks are involved that identify: (1) causality sentences; (2) causality ordering; and (3) causality antecedent and effect consequence pairs.

Step 1: identifies sentences containing causality. In doing so, sentence-level classification is needed and the interpretation of the sentence using linguistic patterns is commonly used. Four linguistic causality expressions proposed by [3, 8, 21] are used for causality identification. These are: (1) causality verb; (2) subordination connective; (3) adverbial connective; and (4) prepositional connective. Table 2 shows more details of each expression with an example sentence.

Table 2 Cue phrases as indicators for causality expressions

Causality expressions	**Cue phrases**
Causative verb	cause, lead (to), bring about, generate, make, force, allow, contribute, make, activate, alert, influence, provide, reduce, relax, result (in), increase, trigger, persist
The engine's loss of power was *caused* by the fuel exhaustion	
Subordination connective	because, as, since, so, so that, once
An accurate average fuel consumption rate for the helicopter was not possible because flying times and fuel records were incomplete.	
Adverbial connective	for this reason, with the result that, hence, therefore, consequently, following
The aircraft proceeded outside the airspace specified for holding. *Consequently*, the aircraft was operated closer to the surrounding terrain.	
Prepositional connective	because of, thanks to, due to, as a consequence, as a result (of)
The engines had stopped *because of* fuel exhaustion	

The causative verb designates the action necessary to cause another action to happen. In the example sentence above, the verb *caused* causes *the engine's loss of power* to happen. Mostly, it encodes the notions of cause-effect in different clauses, that is, the noun phrase, *fuel exhaustion*, expresses the cause while the noun phrase, *the engine's loss of power*, expresses the particular effect. The subordination connective links a causality expression using a subordinator, e.g. *because*. The subordinate clause gives a reason for a conclusion in the main clause. The adverbial connective typically connects causes and effects in different clauses. The prepositional connective connects a noun phrase with a clause or two noun phrases in apposition where a preposition normally relates a nominal member with adverbial function to the rest of a clause [21].

Using the cue phrases in Table 2 as causality connectives to indicate causal sentences, the dataset was analyzed and the results are summarized in Table 3. These expressions cover approximately 74% of the explicit causality expressions found in the dataset when not considering the identification using *others*.

Table 3 Common causality expressions in accident reports

Causality expressions	Number
Causative verb	
result in	36
lead (to)	20
contributed to	17
cause	13
others	78
Total	*164 (41%)*
Subordination connective	
because	43
as	17
others	15

Total	*65 (16%)*
Prepositional connective	
as a result	49
due to	54
because of	13
others	9
Total	*125 (31%)*
Adverbial connective	
consequently	31
therefore	8
following	6
others	4
Total	*49 (12%)*
Total	403 (100%)

The most common causality expression is a causative verb and this accounts for around 41% of the total number of the identified expressions. A slightly lower occurrence is for the prepositional connective at around 31%. This finding is consistent with the general observation that the most common pattern is the use of a causative verb. The output of this step is the decision regarding whether a given sentence is a type of causality sentence and, if so, the sentence is further analyzed in the following step.

Step 2: identifies a correct orientation of causality, i.e. which parts of the sentence denote a cause and an effect. Since the causality expressions can occur in various forms in documents, the strategies for ordering causality are complex. For example, the cause may precede the effect or the effect may precede the cause as shown below:

- An accurate average fuel consumption rate for the helicopter was not possible *because* flying times and fuel records were incomplete. (effect-cause)
- Flying times and fuel records were incomplete. *Consequently*, an accurate average fuel consumption rate for the helicopter was not possible (cause-effect)

The causality ordering is different between clauses of reason and result [21]. In reason clauses, the subordinate clause marks the causal member of the causal relation, while the result is expressed in the main clause. Conversely, in clauses of result, it is the result which is marked in the subordinate clause, and the cause is expressed in the main clause. Adverbial connectives may appear in the sentence initially, medially or finally. The position of the adverbial connective in the sentence affects the scope of the connective and is often associated with the information structure partitioning of the sentence into focus and ground. Table 4 shows the summary of the causality ordering analysis.

The voice of the sentence, i.e. the verb placement in the sentence, is taken into account for the *causative verb* since when the voice is *passive*, the order of cause-effect should be reversed. Passive sentence constructions are transformed into active voice formats in order to correctly determine the ordering. The output of this step is information of the order of cause-effect for the identified causality sentence.

Table 4 A summary of causality ordering

Causality expression	Position	Order of cause-effect
Causative verb		
result in	medial	Cause-Effect (36)
lead (to)	medial	Cause-Effect (20)
contribute to	initial	Cause-Effect (2)
	medial	Cause-Effect (15)
cause	initial	Effect-Cause (2)
	medial	Cause-Effect (11)
Subordination connective		
because	initial	Cause-Effect (8)
	medial	Effect-Cause (35)
as	initial	Cause-Effect (8)
	medial	Effect-Effect (9)
Prepositional connective		
as a result of	initial	Cause-Effect (30)
	medial	Effect-Cause (13)
due to	initial	Cause-Effect (11)
	medial	Effect-Cause (43)
Adverbial connective		
consequently	medial	Cause-Effect (31)
therefore	medial	Cause-Effect (8)

Step 3: extracts the pair of cause and effect that might occur in separate parts or in adjacent parts in a given sentence. The following syntactic information has been derived through the analysis of the annotated sentences:

- Causative verb: both cause and effect are NPs
- Subordination connective: effect is the clause introduced by subordinating conjunction and cause is a simple declarative sentence
- Prepositional connective: cause is a prepositional phrase and effect is a simple declarative sentence
- Adverbial connective: cause is the clause or sentence followed by the adverbial connective and the effect is a separate clause or sentence.

Using the syntactic parse results for sentences, it is relatively easy to automatically extract the cause and effect pair once the information of causality connectives, the causality order and the information above are available. The outcome of the Steps 1-3 is a list of cue phrases each of which is represented with the information regarding causality ordering and the syntactic and sentence structure for cause-effect pair.

Step 4: creates extraction patterns for causality extractions. Using the causality expressions in Table 2, a classifier arranges sentences into either causality or non-causality groups. This classifier is a rule-based system since it makes the classification decision by looking up the existence or absence of the cue phrases in the sentence. A total 55 extraction rules were created for 32 causality expressions. These rules consist of a lexical word and the syntactic constraint of the word. The syntactic constraint is the type of POS tagging and the position of the lexical word in a given sentence. The following shows an example template used for *because*, which is one example of a *Subordination connective*:

Template: *Subordination connective **because***
POS tag: SBAR
Position: *initial*
Ordering: *Cause-Effect*
Syntactic constraint:
Cause: Subordinate clause
Effect: Simple sentence

This rule specifies that if a given sentence is started with the word *because*, and POS tagged as *SBAR*, then this sentence is classified as causality, and the clause introduced by a subordinating conjunction, i.e. *because*, is interpreted as a cause and the simple declarative sentence, is interpreted as an effect.

A test was carried out in order to evaluate the accuracy of the rules. The accuracy was computed by dividing the total number of correctly identified sentences using the rules by the total number of correct sentences in the dataset. A total of 846 causal expressions were identified and 443 identifications were incorrect, resulting in approximately 48% accuracy. It was observed that most ambiguous causality extraction occurs when using the rules of causative verbs. This is because some of them express causality only within a certain context regarding specific semantic relationships between the NPs linked by the verbs. Some causative verbs such as *cause*, *result (in, from)*, *lead to*, or *contribute* were very reliable and no incorrect identifications were made. On the other hand, verbs like *make*, *allow*, *or provide* are ambiguous and more incorrect identifications are likely to be made. For example, on most occasions the verb *allow* means *causality*, but in some cases, it means *grant permission*, as shown in the following sentences. The second sentence is not related to causality. One reason is that it is difficult to infer any relation between *Mandela* and *few visitors*.

(1) More writing space being available for instructions would have *allowed* for larger print.
(2) Mandela was *allowed* few visitors in prison.

In general, a verb is likely to be ambiguous if it has multiple meanings. In this case, the identification of semantic structure is very difficult since no semantic relation is formally indicated between two NPs and the verb [8]. Current approaches to this problem have used: (1) semantic categories of the NPs inferred from the WordNet; and (2) the probability distribution that quantifies the chance of the NP pairs occurring together in the causality sentence. The first method is applicable only if both NPs are defined in WordNet. The second method needs a large-sized tagged corpus to correctly estimate the NPs pair probability.

In this paper, a semantic similarity or relatedness between two NPs is used as a means to detect the existence of causality when the meaning of the verb is ambiguous. This similarity is the measurement of how two NPs are related and if one NP is more related to a given NP than another [25]. In one accident report, for example, *engine* and *fire* are highly related, since *engine* is the source of *fire*. A variety of approaches have been proposed to estimate such semantic similarity and the method proposed by Resnik [27] is used. This method exploits the hierarchy organization of terms, including specialization and generalization relationships, by counting the number of the edges encountered between two NPs when locating them in the hierarchy. For example, the relatedness of *engine* and *fuel* using the Resnik's similarity method is 0.91. When computing the similarity for the NPs which have multiple terms, the final similarity value is a simple product of each term. Table 5 shows Resnik's similarity values between *engine fire* and *fuel starvation* and between *engine fire* and *air traffic*. WordNet::Similarity is a Perl package used for measuring such similarity developed by [25]. By comparing the similarities of both pairs, it is possible to conclude that *engine fire* is more closely related to *fuel starvation*.

Table 5 An example of semantic similarity

NP_1	NP_2	Resnik's similarity
engine	fuel	0.91
fire	starvation	1.70
	Total	*1.55*
engine	air	1.4
fire	traffic	0.52
	Total	*0.73*

The central element in the similarity method is to identify the head or focus term in the NPs. A NP is a phrase whose head noun is a noun or pronoun, and can be accompanied by a set of modifiers, including determiners, e.g. demonstratives, numbers, possessives, quantifiers, and adjectives. A head is a grammatical unit that performs the syntactic function of the phrase. Usually the head noun is the rightmost noun that comes just before the modifier. For example, in the phrase of *more writing space being available for instructions*, *space* is the *head* noun and *more writing* is the modifier.

When analyzing the POS taggings of the NPs, a total of 161 types of NPs was identified in the dataset, and only 19 NPs occurred more than once. On average, each NP consists of nine terms. The most common NP is *DT NN*, e.g. *the DT aircraft NN*. As such, a wide range of syntactic variations is used to describe the NPs, it is difficult to manually create rules for identifying the head nouns.

In this paper, Progol is used to automatically identify such head or focus nouns. As an example of Inductive Logic Programming (ILP), Progol is the intersection of machine learning and logic programming that induces a set of rules specifying under which conditions a positive example becomes true [23]. The rules are in the form of IF-THEN, and are known as more compact, faster and comprehensible when compared to the rules generated by statistical theory only [7]. It has been used for learning extraction rules for NE identification [1], for Web page classification [24], and for semantic annotation [16]. The following shows two examples of rules generated for head noun identification:

prediction(A,B,head) : - dt(A,C), in(B,D).
prediction(A,B,head) : - noun(A,C), vp(B,D), adv(D,E).

A is the left context of the head noun and B is the right context. Using the first rule, the term *circumstances* is predicted as the head noun when testing with the sentence of *the/DT circumstances/NNS of/IN the/DT fuel/NN exhaustion/NN*. dt(A,C) is true if A starts with a determiner, e.g. *a*, *the*, and in(B,D) holds if B is a preposition phrase. Similarly, using the second rule, *space* is predicted for the sentence of *more/JJR writing/NN space/NN being/VBG available/JJ for/IN* *instructions/NNS*. This rule specifies that the *space* is the head noun if the left context of it is a noun, and if the right context is a verb phrase followed by an adverb phrase. A total of 25 head noun identification rules were created, and the identified noun is used as a basis for computing the semantic similarity. The extraction rules for some of causative verbs are then extended in order to make use of the similarity value for correctly identifying causality sentences. The following shows an example of the extended rule for the *allow* verb:

Template: *Subordination connective* ***allow***
POS tag: VBD, VBG
Position: *medial*
Ordering: *Cause-Effect*
Syntactic constraint:
Cause: Noun phrase, NP_1
Effect: Noun phrase, NP_2
Semantic constraint:
$sim(head(NP_1), head(NP_2)) > threshold$

$sim(head(NP_1), head(NP_2))$ is the semantic similarity value between the head nouns in NP_1 and NP_2 . Threshold is pre-defined numeric value used to compare the similarity between two NPs.

Figure 4 shows the graphic user interface used for annotating example sentences from which the extraction rules are derived. This interface initially suggests the sentences that match with one of the causality expressions in Table 2 in order to ease the task of the manual annotation. A human annotator reviews the initial extractions and modifies, deletes or adds new examples. It consists of: (1) a button for opening a new text; (2) a button for highlighting the matched causality sentences; (3) a panel showing the matched sentences with colouring; (4) a list of causality sentences numbered in the order of their occurrence in the example text; (5) the detail of each matched sentence, i.e. the causality connective that is used to signal the causality; and the parts of the sentence representing a cause and an effect; and (6) a button for adding a new example. The interface was developed using the Java programming language.

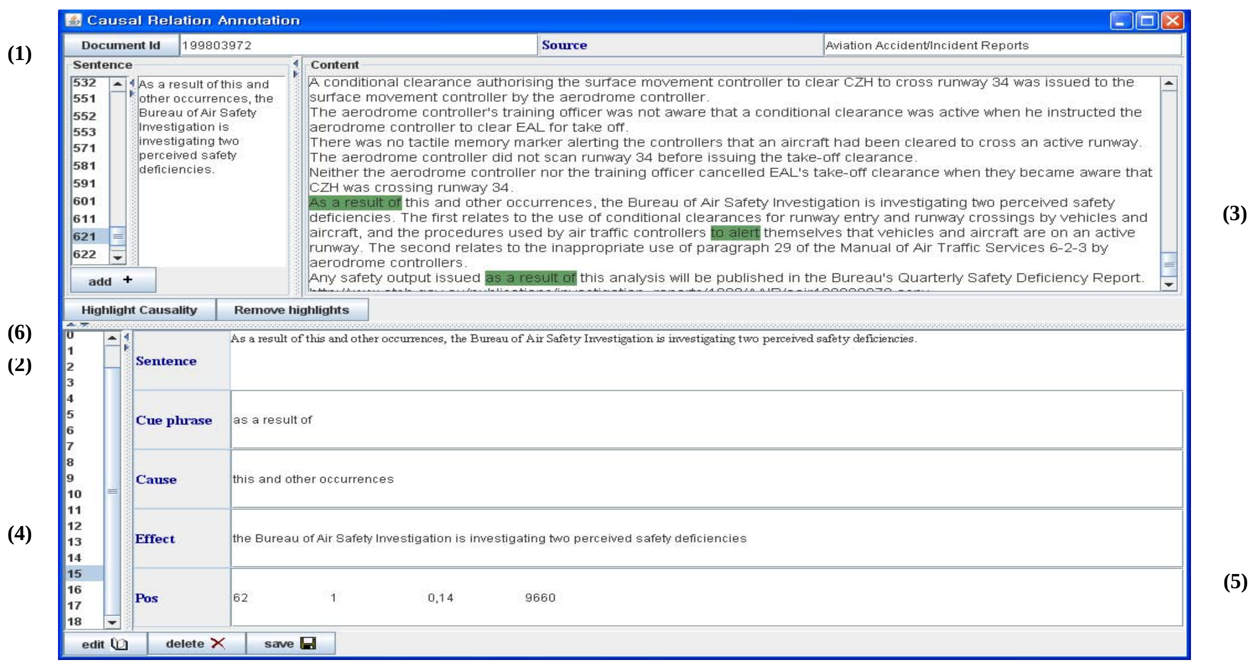

Figure 4. A user interface used for a manual annotation

3.3.3. Evaluation of causality extraction

This evaluation tests the applicability of the extraction rules especially generated for causative verbs. Ten new aviation accident and incident reports were downloaded from website of http://www.tsb.gc.ca/. Each report was analyzed using the four steps in Section 3.3.1. A total of 242 paragraphs with 903 sentences was extracted. A total of 201 causality expressions from 179 sentences was annotated. Approximately, 20% of sentences in a single report are causality sentences. The total numbers for each causality expression type were: causative verb = 63, subordination connective = 53, prepositional connective = 26, and adverbial connective = 59. The following are the most commonly occurring causative verbs: *cause, contribute (to), affected, result (in), and lead (to).*

The pattern matching for each 63 expression proceeds with the following steps: (1) cue phrases that match with keywords in the sentence are identified; (2) extraction rules associated with each matching cue phrase are identified; and (3) for each identified rule, a matching process is carried out on the sentence. Precision and recall were used to measure the performance of the proposed approach. Precision is the percentage of the automatically identified expressions that are identified as right among the total number of identified expressions. Recall is the percentage of the automatically identified right expressions among the total number of right expressions

On average, 72% precision and 67% recall was achieved. The threshold for comparing semantic similarity was set as 0.5 meaning that the expressions which had semantic similarity values over 0.5 were selected. The most improved performance was made on the *made* verb. In the dataset, a total of 18 sentences were matched with *made*, but only 5 of them actually represented causality. Using the extraction rules, six sentences were matched, and among them 4 sentences were correct predictions, resulting in 67% precision and 80% recall. The performance is a significant improvement in compared to 28% accuracy, i.e. 5 from 18.

The examination of extraction errors made by the proposed approach reveals the importance of robust syntactic parsing, especially when converting a given sentence into a subject-verb-object triple. In this research, the Apple Pie Parser was used for generating syntactic parse trees. Whereas the parser is fast, it was observed that it tends to generate incorrect parses, especially for the verb phrases containing words normally functioning as nouns. To address this, a manual correction is necessary before sending sentences to the Apple Pie parser.

Although this evaluation is on a small scale, it indicates that the proposed approach achieves a respectable result using a limited linguistic resource. In addition, due to its relative simplicity and ability to run over small amounts of training data, the approach demonstrates potential useful in industries.

4. CONCLUSIONS AND FUTURE WORK

This paper has presented a framework for automatically extracting causality expressions from aviation accident or incident reports. Particular attention was given on extracting explicitly defined causality expressions. Based on the analysis of example reports, it was observed that the most confusing causality was due to causative verbs whose meanings vary depending on context. Deep linguistic analysis would be helpful for disambiguating the correct meanings of the verbs. However, since it requires extensive knowledge of computational linguistics, the development of such an analysis method is a challenge for most engineering organisations. To address this problem, this paper has used a similarity measurement for estimating semantic relatedness of two NPs in order to identify whether the given verb signifies causality. When testing with ten new accident reports, the proposed approach achieved 72% precision and 67% recall, which were significantly better than the 48% accuracy discussed in Section 3.3.2.

Causality is an important knowledge in many of engineering applications. Approximately, 20% of sentences in a single aviation accident or incident report are causality expressions. Through the empirical analysis of the dataset, we identified most of causality expressions could be extracted using shallow linguistic patterns.

Most causality expressions entail evidence used to justify the causality. Using the dataset in Section 3.2, this research has identified that the evidence sentence can be most easily detected by using the verb *indicate* and its synonyms, e.g. *suggest*, *hint*, *highlight*, *found*. The extension of the proposed approach to extract such evidential sentences is being investigated. In particular, the development of graphical representations of summarising and linking all relevant evidence and claims is of considerable interest to us. The need to develop a suitable delivery mechanism that helps engineers to understand better the linear descriptions of events has been mentioned in literature, but no progress has yet been made on this.

It is known that it is difficult to achieve a high level of agreement between individuals regarding whether a certain sentence really conveys causality, i.e. about 64%. Researches have therefore tried to identify the core properties of causality and develop one query to test is the degree of co-dependency between cause and effect. In doing so, the modality of causality, e.g. , *the cause of, the most likely cause of, the root cause of*, could be useful. An extension of the proposed approach to accommodate such modality is planned.

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REFERENCES

[1] Aitken, J. S.: Learning information extraction rules: An inductive logic programming approach. In European Conference on Artificial Intelligence ECAI, France, 335-359, 2001.

[2] Allen, J. Natural Language Understanding. Benjamin/Cummings Publishing Company, Inc., 1987

[3] Altberg, B. Causal Linking in Spoken and Written English, In Studia Linguistica, 38 (1), 1984.

[4] Bruseberg A. and Johnson P. Understanding Human Error in Context: Approaches to Support Interaction Design Using Air Accident Reports, In 12th Int. Symposium on Aviation Psychology,,U.S.A.,166-171, 2003.

[5] Chang, D. and Choi, K.: Incremental cue phrase learning and bootstrapping method for causality extraction using cue phrase and word pair probabilities, In Information Processing and Management. 42(3): 662-678, 2006.

[6] Cole, S. V., Roya, M. D., Valtorta, M. G. and Huhns, M. N. A Lightweight Tool for Automatically Extracting Causal Relations from Text, In IEEE Southeastcon, 2006.

[7] Cussens, J. Part-Of-Speech Tagging Using Progol, In the 7th International Workshop on Inductive Logic Programming, pp.83-108, 1997

[8] Girju, R. Automatic detection of causal relations for question answering. In the 41st annual meeting of the association for computational linguistics, workshop on multilingual summarization and question answering--Machine learning and beyond, Sapporo, Japan, 2003.

[9] Grishman, R Information Extraction: Techniques and Challenges, In Lecture Notes in Artificial Intelligence, Vol. 1299, 1997.

[10] Johnson C. A First Step Towards the Integration of Accident Reports and Constructive Design, Documents. In SAFECOMP, 1999.

[11] Kaplan, R. M., and Berry-Rogghe, G. Knowledge-based acquisition of causal relationships in text. Knowledge Acquisition, 3(3), 317-337, 1991.

[12] Khoo, C. S., Chan, S., and Niu, Y. Extracting Causal Knowledge from a medical database using graphical patterns, In the 38th Annual Meeting on Association for Computational Linguistics, Hong Kong, pp. 336-343, 2000.

[13] Khoo, C. S., Kornfilt, J., Oddy, R. N. and Myaeng, S. H. Automatic Extraction of Cause-Effect Information from

Newspaper Text without Knowledge-based inferencing, In Literary and Linguistic Computing, 13(4):177-186, 1998.

[14] Kim, J. Causes and Effects: Mackie on Causation, In Causation, Oxford Readings in Philosophy, ed. Ernest Sosa and Michael Tooley, 1993.

[15] Kim, S. and Baldwin T. Automatic Interpretation of Noun Compounds using WordNet Similarity, In the Second International Joint Conference on Natural Language Processing, South Korea,2005.

[16] Kim, S., Bracewell, R. H. and Wallace, K. M. From discourse analysis to answering design questions, In EKAW 2004, International Workshop on the Application of Language and Semantic Technologies to support Knowledge Management Processes, Whittlebury Hall, Northamptonshire, UK, 43-49, 2004.

[17] Kim, S., Bracewell, R. H. and Wallace, K. M. Answering engineers' questions using semantic annotations', In AIEDAM Special Issue on Computational Linguistics for Design, Maintenance and Manufacturing, 12, pp.155-171, 2007.

[18] Liddy, E. D. Enhanced Text Retrieval Using Natural Language Processing. In Bulletin of the American Society for Information Science and Technology, 24(4), 14-16, 1998.

[19] Macus, M.P., B. Santorini, M., Marcinkiewicz, A. M.: Building a Large Annotated Corpus of English: The Penn Treebank. In Computational Linguistics. 19(2). 313-330, 1994.

[20] Marcu, D., and Echihabi, A. An unsupervised approach to recognising discourse relations. In the 40th Annual Meeting of the Association for Computational Linguistics, pp. 368-375. U.S.A., 2002

[21] Meier, E. A. Contrastive Study of Causal Subordination in English and Norwegian, PhD Thesis, University of Oslo, 2001.

[22] Miller, G. A., Beckwith, R.W., Fellbaum, C., Gross, D., and Miller, K.: Introduction to wordnet: An on-line lexical database, In Int. Journal of Lexicography, 3(4), 235-312.16. 1993.

[23] Muggleton, S. Inverse Entailment and Progol, In New Generation Computing, 13:245-286, 1995.

[24] Parson, R. and Muggleton, S. An experiment with browsers that learn, In K. Furukawa, D. Michie and S. Muggleton (Eds.), Machine Intelligence, 15, Oxford University Press, 1998.

[25] Patwardhan, S., Banerjee, S., and Pedersen, T. Using Measures of Semantic Relatedness for Word Sense Disambiguation, In the Fourth International Conference on Intelligent Text Processing and Computational Linguistics, Mexico City, 2003

[26] Pechsiri, C., Kawtrakul, A., and Piriyakul, R. Mining Causality Knowledge From Textual Data, In the 24th IASTED International Multi-Conference Artificial Intelligence and Applications, Austria, 85-90, 2006.

[27] Resnik, P. Using Information Content to Evaluate Semantic Similarity in Taxonomy. In the 14th Int. Joint Conf. on Artificial Intelligence, 448-453, 1995.

[28] Sekine S., and Grishman R. A Corpus-Based Probabilistic Grammar with only two Non-Terminals, In Fourth Int. Workshop on Parsing Technologies. 216-223, 1995.

[29] Selfridge, M., Daniell, J., and Simmons, D. (1985) Learning causal models by understanding real-world natural language understanding, In the Second Conferences on Artificial Intelligence Applications: The Engineering of Knowledge-based systems, 378-383, 1985

[30] Shin I., Kim S., Busby J. S. Hibberd R.E. and McMahon C.A. An application of semantic annotations to design error. In IEEE International Conference on Hybrid Information Technology, Korea, (in press), 2006.

[31] Takashi,I. Kentaro, I. and Yuji M. What Kinds and Amounts of Causal Knowledge Can Be Acquired from Text by Using Connective Markers as Clues?, In International Conference on Discovery Science, 180-193, 2003.

[32] Turney, P. D.: Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews. In Proc. 40th Association of the Computational Linguistics (ACL), U.S.A, 417-424, 2002

[33] Wiebe, J., and Riloff, E. Creating Subjective and Objective Sentence Classifiers from Unannotated Texts. In Int. Conf. on Computational Linguistics and Intelligent Text Processing, Invited Paper, Springer LNCS Vol. 3406, 2005.

[34] Wiegmann D. A. and Shappell. S. A. A Human Error Analysis of Commercial Aviation, Accidents Using the Human Factors Analysis and Classification System (HFACS), Technical, In Technical Report of Federal Aviation Administration, 2001.

[35] Software Tools for NLP, available at http://www-a2k.is.tokushima-u.ac.jp/member/kita/NLP/nlp_tools.html

