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Research Article

Aspect Level Sentiment Analysis Methods Applied to Text in Formal Military Reports

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ABSTRACT:

Many military functions such as intelligence collection or lessons learned analysis demand an understanding of situations derived from large quantities of written material. This paper describes approaches to gain greater understanding of document content by applying rule-based approaches in addition to open source machine learning models. The performance of two approaches to sentiment analysis are assessed, when operating on document sets from NATO sources. This combination enables analysts to identify items of interest within large document sets more effectively, by indicating the sentiment around specific aspects (nouns) which refer to a specific target (noun) in the text. This enables data science to give users a more detailed understanding of the content of large quantities of documents with respect to a particular target or subject.

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Introduction

The military operational community is becoming aware of the potential for data science to empower their speed and accuracy of decision making when using vast numbers of datasets – such as documents coming from military operations

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and exercises, or publicly available data sets – that are relevant for situational awareness.

One of the most interesting and challenging techniques that can enrich analysis of document collections, and provide valuable answers is sentiment analysis. Sentiment analysis – analysing people's opinions, sentiments, appraisals, attitudes, and emotions toward specific entities such as services, objects or individuals.[1] These aspects are often expressed in textual documents and are used by analysts to help identify the most relevant information from documents. Sentiment analysis can be done on different levels of document granularity; overall sentiment across the whole document, over a paragraph or a sentence. More specifically, sentiment can be defined towards a specific target which can be an entity, keyword or term of interest. This level of sentiment analysis provides additional insight and sentiment polarities (positive or negative) on each different aspect (or target), significantly enhancing the value extracted from documents.

Aspect-based sentiment analysis (ABSA) has recently become one of the most interesting areas of research in the field of sentiment analysis but has not previously been applied to military document sets.

Sentiment analysis in a military environment can be interesting from different operational perspectives:

- Missions and exercises: Expression of sentiment on collaboration platforms and formal reports can indicate lessons or best practices that should be identified;[2]
- Public media or *Information Environment Assessment*: Formal and social media sources can indicate sentiment towards NATO, military forces or missions; or
- On site population surveys during NATO missions.

During analysis of NATO related reports and documents, the sentiment towards target was found to be particularly interesting because it provided a richer context, for example negative sentiment can direct us to sources of potential problems, positive sentiment may indicate best practices.

This paper explores different methods of "sentiment analysis towards target" on NATO related document sets.

Approach

Many researches and studies on sentiment analysis are based on publicly available corpora e.g. movie (e.g. iMDB) and product reviews. This dataset is often annotated and is used as a training dataset for supervised machine and deep learning models to further classify sentiment specifically for that information environment.

Documents and reports relevant for military environment have a more formal narrative and very often use complicated sentence structures. Annotation of this type of document/dataset is demanding and resource intensive, but does not guarantee quality end results. Absence of annotated datasets led us to explore and test alternative solutions other than training machine learning models.

In our experiment we used two approaches:

- Sentiment towards target based on neighbouring sentiment terms; and
- Sentiment towards target using syntactical dependency relation.

Datasets

Sentiment analysis was performed on three document sets related to the NATO environment:

- Documents from NATO Lessons Learned Portal including Lessons Learned and reports;
- Documents from a NATO exercise, including collaboration services;
- Surveys of public opinion during a NATO mission.

Additional datasets containing a sentiment lexicon developed by NATO analysts, and NATO terms and glossaries were used to enrich and customize the analyses.

Document Pre-processing and Tools

For data ingestion, pre-processing, advanced analytics and Natural Language Processing (NLP) we used the KNIME Analytics Platform (KNIME),[3] an open source data science tool containing many out-of-the-box functions covering the whole data science process. Sentiment analysis tasks also used built-in Stanford NLP models. All of which followed extensive pre-processing.

Pre-processing steps:

1. Cleaning of documents using regular expressions and stop-word dictionary;
2. Part of Speech (POS) tagging based on Stanford pre-trained machine models. The terms in the documents are labelled with the predicted part of speech e.g. noun, verb or adverb;
3. Tagging Named Entities (NE) using Stanford NE tagger and custom developed dictionaries; and
4. Dictionary taggers using Sentiment Lexicon and terms.

Sentiment Towards Target Based on Neighbouring Sentiment Terms

Sentiment toward target is determined by matching sentiment terms with neighbouring terms to the target term. Sentiment terms are defined in the Sentiment Lexicon and contains a list of polarity words that express positive, negative and neutral sentiment important to our domain. Neighbouring terms represents n consecutive terms, counting both left and right from the targeted term, where n is usually set to between 3 and 5 neighbouring terms.

Methodology

1. Extraction of sentences from documents using Stanford NLP sentence extractor;

2. Extraction of neighbouring terms for each word in the sentence;
3. Matching neighbouring terms with sentiment terms; and
4. Matching sentence terms with target term (using Name Entity Extraction).

The final result of these steps is a list of sentences with related target terms and their sentiment terms and sentiment scores.

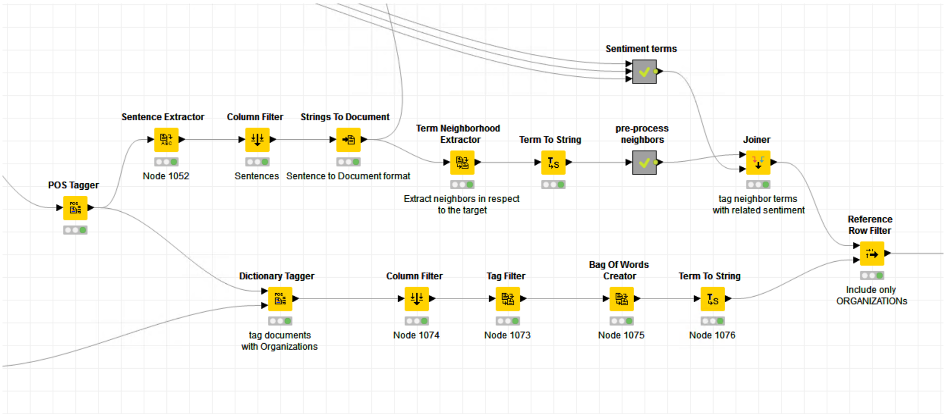


Figure 1: Workflow in KNIME for extracting sentiment towards target.

This method was performed on a data set from the NATO Lesson Learned portal where we targeted organizations, to analyse the sentiment towards them.[4] Named Entity Recognition was used to recognise organisations; sentiment analysis was then applied towards the target of these organisations as an algorithm searched for neighbouring terms indicating sentiment. This – aggregated per organization – resulted in sentiment values found alongside the organizations, showing percentages of positive, neutral and negative terms and indicating sentiment towards the organization: the "target" (Fig. 2).

Assessment of Sentiment Using Neighbouring Terms

This technique does not provide an understanding of the semantic context of a document but it can quickly point to the part of document referring to the target and those sentiment terms worthy of further investigation by users.

This method has the following disadvantages:

- It is difficult to determine the optimal number of neighbouring terms to define sentiment polarity of a target; the number depends of the sources of text being analysed;
- It is not reliable that the target term is the aspect of the sentence, and that sentiment term is referring to that certain aspect.

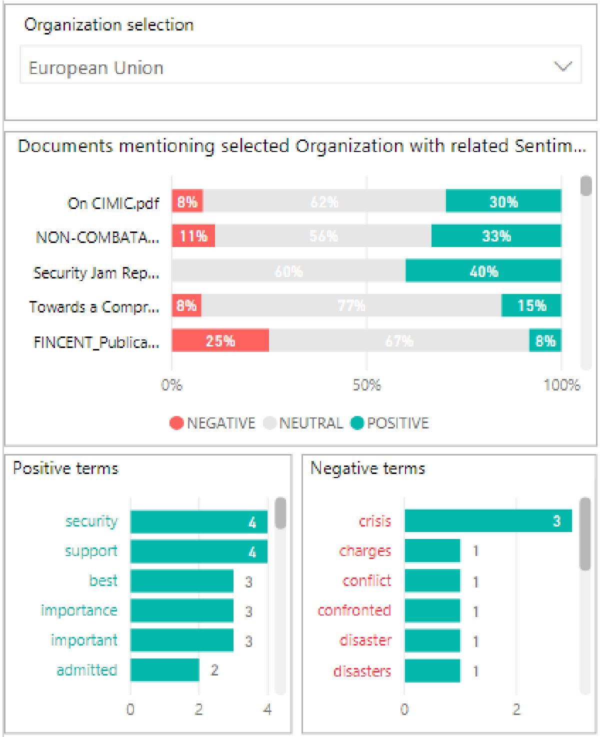


Figure 2: Sentiment analysis (neighbouring terms).

Sentiment Towards Target Using Syntactic Dependency Relations

To address these deficiencies, we explored syntactic dependency relations between words in the sentence. Syntactical dependency relation provides information of how words grammatically relate to each other in the sentence. There are many types of relations that can be extracted from the sentence, and in this work we will focus only on the subset of dependency relations that are relevant for our task to identify the target and related sentiment. Using this concept we tested the following hypothesis:

If we are able to determine the target of the sentence with related sentiment terms, then we can determine sentiment to that target in the sentence.

The most important task was to efficiently identify and extract targets and sentiment words related to the target from documents. Using the dependency relation approach, a word may be a candidate target or sentiment word, based on the type of dependency relation and the part-of-speech (POS) tag of the word in that relation.[2]

Methodology

The methodology to identify target in the sentence and related sentiment towards the target used the following steps:

- Document pre-processing (preparing documents for NLP tasks);
- Co-reference resolution;
- Splitting of sentences;
- Dependency parsing;
- Dependency relation analysis – Determining target and sentiment based on syntactical rules.

This methodology is rule-based and it relies on accuracy of the dependency parser used.

Co-reference Resolution

Co-reference resolution is the task of finding all expressions that refer to the same entity in a text.[5] In this context, such expressions are called mentions, or anaphoric noun phrases. The process of linking together mentions that relate to real world entities is called co-reference resolution. Mentions can be either named, nominal or pronominal. Co-reference resolution is an important step for higher level NLP tasks that involve natural language understanding such as document summarization, question answering, and information extraction. This is an important task for our work in order to ensure that every mention of a potential target and its related sentiment is captured.

For our implementation we used the Stanford CoreNLP implementation called CorefAnnotater.[6] The CorefAnnotator finds mentions of the same entity in a text, such as when "Theresa May" and "she" refer to the same person. For example, the mentions "Obama", "the president", and "he" could all refer to Barack Obama. The annotator implements both pronominal and nominal co-reference resolution. Pronominal co-reference resolution chains named entities to their pronouns. Nominal co-reference resolution chains named entities to its noun references. Figure 3 shows how pronominal co-reference resolution operates, where the pronoun "he" refers to "Our new president" and "it" to "corruption."

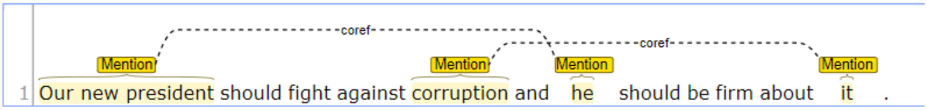


Figure 3: Example of co-reference resolution.[10]

Dependency Parsing

To determine syntactical dependency relations between words, we used dependency parsing.[7] Dependency parsing extracts a dependency tree of a sentence that represents its grammatical structure and defines the relationships between governor and dependent, which modify those governors. Governor and dependant are often referred to as a parent and child relationship. Children of a parent word are said to depend on the parent (governor). Adjectives typically appear in a dependency tree close to the nouns they describe, often as direct parents or children. The dependency relation represents the grammatical relationship between the governor and dependent words.

Clausal Argument Relations	Description
NSUBJ	Nominal subject
DOBJ	Direct object
IOBJ	Indirect object
CCOMP	Clausal complement
XCOMP	Open clausal complement
Nominal Modifier Relations	**Description**
NMOD	Nominal modifier
AMOD	Adjectival modifier
NUMMOD	Numeric modifier
APPOS	Appositional modifier
DET	Determiner
CASE	Prepositions, postpositions and other case markers
Other Notable Relations	**Description**
CONJ	Conjunct
CC	Coordinating conjunction

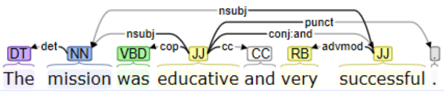
Figure 4: Selected dependency relations from the Universal Dependency set.[7]

In this work we used the Stanford dependency parser implementation to generate sets of syntactic dependencies. Stanford dependencies [8] are represented as triplets of:

- Relation type;
- Governor – main syntactic and semantic properties are inherited from this;
- Dependent (depends on the governor word).

The dependency relation contributes to the identification of potential sentiment words and the aspect-sentiment word pairs, also known as *opinion pairs*.

In our work we used following Type Dependency Relation (TDR) and related rules to extract target and sentiment extraction, as listed in table 1. In table 1 each row contains a relation type and part of the relation (*governor* or *dependent*) which is associated to *sentiment term* and *aspect(target)*. The complement represents a related relation of which *governor* or *dependent* complete an *opinion pair*. In addition to the *dependency relation*, Part-of-Speech (POS) tags are also taken into account for more accurate identification of aspects and sentiment. All relation types are explained in detail in Universal Dependency Relations,[9] this comes from the Universal Dependencies (UD) framework for consistent annotation of grammar (parts of speech, morphological features, and syntactic dependencies) across different human languages.



root(ROOT, educative)
det(mission, The)
nsubj(educative, mission)
nsubj(successful, mission)
cop(educative, was)
cc(educative, and)
advmod(successful, very)
conj:and(educative, successful)
punct(educative, .)

Figure 5: Example using Stanford dependency tree [10] and triplets.

In our work we used following Type Dependency Relation (TDR) and related rules to extract target and sentiment extraction, as listed in Table 1, on the sentence "The **mission** was *educative* and *very successful*" we can extract target and sentiment using following relations:

- nsubj(educative, mission)
- nsubj(successful, mission)
- advmod(successful, very)
- conj:and(educative, successful)

Where the *target* is **mission** and *sentiment* is v**ery successful** and **educative**.

Experiment Results

Sentiment towards target using syntactic dependency relations (SDR) method has the functionality to extract both *target* and *sentiment* whereas the *Sentiment towards target based on neighbouring sentiment terms (NST)* method, target should be defined using other techniques such as labelling targets using Dictionary tagger or Name Entity Recognition tagger. This makes it more complicated to make a direct numerical comparison of results from the two methods so the results are compared to assessment by a human expert.

For the purpose of experiment, fifty sentences – with differing levels of complexity – expressing sentiment were extracted from data collections mentioned in "Datasets." The number of sentences was limited due to the fact that human assessment needed to be done on each sentence in order to provide a comparison to the syntactic dependency and neighbouring sentiment terms method.

	Sentiment term (JJ/VB/RB)	**Aspect** (NN, NNS, NNP)	**Comple-ment**	**Opinion pair (sentiment, target)**
NSUBJ	Governor	Dependent		(Governor, Dependent)
NSUBJ-PASS	Governor	Dependent		(Governor, Dependent)
XCOMP	JJ: Depend-ent/ Gover-nor	NSUBJ (Dependent)	NSUBJ	(Dependent/Governor, NSUBJ(Dependent))
DOBJ	Governor (VB)	Dependent (NN)		(Governor, Dependent)
AMOD	Dependent	Governor NN: Dependent	NSUBJ	(Dependent , Governor) (NSUBJ(Governor), Dependent, Governor)
ADVMOD	Dependent, Governor		NSUBJ	((Dependent, Governor), NSUBJ(Dependent))
ACL	Dependent	Governor		(Dependent , Governor)
NMOD	JJ: Governor	NN: Dependent; NN: Dependent, Governor		(JJ: Governor, NN: Dependent)
COMPO-UND		NN: Dependent, NN: Governor	NSUBJ/ DOBJ	(NSUBJ(Dependent), Dependent, Governor)
NEG	Dependent, Governor		NSUBJ/ DOBJ	((Dependent, Governor), NSUBJ(Dependent))
CONJ	Dependent, Governor	NN: Dependent, Governor	NSUJB/ DOBJ	((Dependent, Governor) + NSUBJ /DOBJ(Dependent), (Dependent, Governor)+ NSUBJ /DOBJ(Governor))

Table 1. Aspect/Sentiment Extraction Rules.

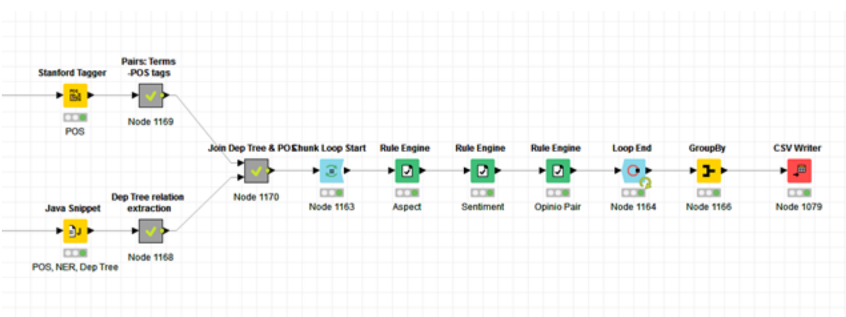


Figure 6: KNIME workflow for extracting aspects and sentiment using syntactic dependency method.

Figure 6 shows the KNIME implementation used to generate the experiment results. For the sentence: *"The **colleagues** from the **mission** were always **prompt** in providing **accurate** and **appropriate answers** to all my **urgent requests**."* The algorithm extracted the following relations and Parts-of-Speech:

Relation Type	Governor	Dependent	Governor POS	Dependent POS	Aspect	Sentiment	Opinion Pair
det	colleagues-2	The-1	NNS	DT			
nsubj	prompt-8	colleagues-2	JJ	NNS	colleagues-2	prompt-8	colleagues-2, prompt-8
case	mission-5	from-3	NN	IN			
det	mission-5	the-4	NN	DT			
nmod:from	colleagues-2	mission-5	NNS	NN	mission-5, colleagues-2		
cop	prompt-8	were-6	JJ	VBD			
advmod	prompt-8	always-7	JJ	RB			
mark	providing-10	in-9	VBG	IN			
advcl:in	prompt-8	providing-10	JJ	VBG			
amod	answers-14	accurate-11	NNS	JJ	answers-14	accurate-11	accurate-11, answers-14
cc	accurate-11	and-12	JJ	CC			
conj:and	accurate-11	appropriate-13	JJ	JJ		appropriate-13, accurate-11	
amod	answers-14	appropriate-13	NNS	JJ	answers-14	appropriate-13	appropriate-13, answers-14
dobj	providing-10	answers-14	VBG	NNS	answers-14	providing-10	answers-14, providing-10
case	requests-19	to-15	NNS	TO			
det:predet	requests-19	all-16	NNS	DT			
nmod:poss	requests-19	my-17	NNS	PRP$			
amod	requests-19	urgent-18	NNS	JJ	requests-19	urgent-18	urgent-18, requests-19
nmod:to	providing-10	requests-19	VBG	NNS			
root	ROOT-0	prompt-8		JJ			

Figure 7: Extracted aspects, sentiment and opinion pair.

From Figure 7 we can read the following:

- Aspects(targets): "mission colleagues," "answers," "requests";
- Sentiment: "prompt," "accurate," "appropriate," "providing," "urgent";
- Opinion pairs: "prompt colleagues," "accurate answers," "appropriate answers," "answers providing," "urgent requests."

In the above example, human assessment gave the same results as the rule based algorithm.

Overall performance of the algorithm was measured by calculating the number of correctly extracted aspects in comparison to wrongly recognised aspects. The same rule was addressed to sentiment terms, shown below.

Table 2: Results.

	Positive	False positive	Accuracy
Aspect terms SDR method	122	12	90.16%
Sentiment terms SDR method	93	25	73.1%
Aspect terms NST method	90	44	51.1%
Sentiment terms NST method	78	40	51.3%

This gives an accuracy for *syntactical dependency relation* method of recognizing aspects in this small subset of documents of around 90 %, compared to an accuracy of recognizing sentiment of around 73 %. Using *neighbouring sentiment terms* method results are much less accurate giving us accuracy for targets around 51 % and the same percentage for sentiment.

If we analyse results by number of aspects in the sentence it is immediately visible that sentences with simple structure and less aspects have almost zero false positives for both, aspect and sentiment in syntactical dependency method. Sixteen sentences from the overall experiment set with a simple structure (1 or 2 aspects) have an accuracy of 93.8% for aspects and sentiment terms.

Conclusions

Comparing the two approaches explored in this paper, the conclusion is that using the syntactic dependency relation between terms provides better and more reliable results on SA than just considering neighbouring terms. Additionally, the *syntactic dependency* method recognizes the aspects of the sentence which directly relate to the sentiment expressed leading to more useful results for the end users.

The *syntactic dependency* approach may be improved by including additional dependency relations between terms, in addition to the relations listed in Table 1. This may increase the probability of accurately recognising the correct sentiment and target.

Also, considering that sentences with simple structure have better accuracy, improvement may also be achieved by analysing complex sentences and splitting them into simple knowledge statements that contain no more than 1 or 2 aspects. This can be interesting for further exploration in this area.

The *syntactic dependency* approach provides greater certainty regarding the sentiment expressed about specific targets within the text. This leads to a tool which provides a more useful service to users, allowing them to identify sentiment more accurately towards more specific targets. This provides additional value to users when they seek to extract valuable information from document sets so large that data science tools are the only practical method to assess them.

Syntactic dependency could also be used to annotate positive or negative sentiment (and confidence level) within document sets which could be subsequently used to train machine learning models for sentiment analysis. Currently, the lack of annotated text from military sources limits the use of effective machine learning for this task.

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