Using Argument Analysis to Define a Structure for User Generated Content

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ABSTRACT
Within the internet there are several good information sources which can provide facts and general information, but it is less obvious where to find meaningful discussions and arguments that are grounded with evidence. The objective of this work is to automatically identify and extract the structure of arguments from user added content. The hypothesis is that this can be used to identify where a specific user should add their own content. Allowing the users of content to see the structured arguments contained within that content, with the claims, counter claims, replies and grounds, allows the users to navigate the content. This can facilitate knowledge acquisition and enables the user to become part of the conversation in a way that is arguably more useful to them.

Categories and Subject Descriptors
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1. INTRODUCTION
The scientific method requires that empirical and measurable evidence can be found to support a hypothetical explanation of a phenomenon. The hypothesis can be used to predict the outcomes in a certain scenario, which can then be evaluated through evidence. Academics can test their theories through discussion; allowing the evaluation of a hypothesis with regard to evidence provided by others. Conversation, or discourse, is how people compare ideas, solve problems and identify disagreements as part of daily life.

An argument is a conversation which involves different points of view. The initial point of view is a claim and this claim can be countered with another claim. The claims are backed up with evidence which can also be referred to as grounds. An individual constructs an argument claim that represents their position, in this they explain to others the evidence that has led to their position (the claim and the grounds that they use to support this). A counter claim challenges the original position, providing further evidence or information. This is intended to cause the composer of the original claim to re-evaluate their position and accept the counter claim. Those who have been involved in the argument have been made aware of other perspectives on the original problem thus allowing the participants to gain new knowledge that may change or confirm their perspective, encourage them to conduct further investigation, or they may use this evidence to solve other problems at a later date.

In traditional print media journalists, academics and other writers perform the tasks of collating and curating information to present in a structured way to consumers. These professionals summarise the debates and add in their own claims and evidence. The consumer of this content is then free to consult this evidence and determine their own beliefs. In the Internet domain there is an overwhelming amount of information available, some is collated and curated in this manner but much is not. There are several good information sources which can provide facts and general information but it is less obvious where to find meaningful discussions and arguments that are grounded with evidence.

Tools are freely available that allow users to be both producers and consumers of content and to be part of the wider internet conversation. Users add data to social networking sites, they use the ‘add comments’ sections of news articles, they blog or micro blog and they contribute to articles for information collation sites such as Wikipedia. The discussions that occur in these conversations must be evaluated by humans because the argument structure is not presented explicitly and therefore cannot be automatically analysed. If a user wishes to hear all sides of an argument (the full argument space) it can be difficult to find all the right information.

Looking for information in the wrong places can give a skewed version of the argument. Most user generated content systems allow users to comment in a linear way, as a list with each addition being added to the top or the bottom of the list. Additionally many sites allow users to comment upon the comments of other users, thereby creating a thread...
like structure. Often this data is presented by time of addition, so the user sees the most recent added data first, or by a user rating system, often represented using votes for or against particular data (comment systems) or by the repeting information (blogs, twitter). Unfortunately the speed with which comments are added is extremely variable and this makes it difficult to follow the conversations and for users to comment at the most appropriate locations. The volume of data can be overwhelming therefore users may adopt the approach of only reading what they are interested in. This can lead to cyberpolarization where users with opposing opinions are not aware of the evidence from the opposing side [4,7]. Often the users only look at the most popular or the most recent content, depending on the display system used, and therefore can form a misleading impression of the overall discussion.

Users who post moderate, well-thought-out opinions are often shouted down by extremists and discussions can often end with neither side appreciating the other point of view and even becoming insulting, these are called flame wars [7]. This can lead to those with interesting opinions not posting as they fear they will either not be read or they will be shouted down and insulted. The current thread style is no longer a good interface for interacting with this user generated data [2].

If the user is able to determine their position from the evidence available it is then difficult to determine the most useful location to add their own information so it can be found by others. Allowing the users of content to see the structure arguments, with the claims, counter claims, replies and grounds, allows the users to navigate the content. This can facilitate knowledge acquisition and enables the user to become part of the conversation in a way that is arguably more useful to them.

Digital libraries support scholarly enquiry through search tools. There is no clear way to see an overview of the opposing sides of a discussion. A user must read many journal papers or blogs and have conversations with specialists in the areas they wish to investigate. Conversations can be conducted online through commenting on specific papers or blogs or identifying the experts through social networking tools and contacting them directly. A tool that analyses these conversations to determine the structure of the discussion would make the content easier to navigate and make these conversations available for vicarious learning, thereby, increasing the usefulness of this content and aiding scholarship.

The objective of this work is to automatically identify and extract the structure of arguments from user generated content. The hypothesis is that this can be used to identify where a specific user should add their own content. The general aims of such systems are to support as much expressiveness as possible about the discussions whilst still retaining usability.

2. PREVIOUS WORK

Argumentation is used by systems which implement process such as agent reasoning, web negotiation and also in logical programming which uses argumentation that employs logic. In 1958 Stephen Toulmin [25] noted that natural human argumentation differs from these logics but shares the same basis of claims and evidence. From this Toulmin identified that formal logic was different from that used in academic discussion. He produced a model of this style of argumentation and founded the modern study of argumentation to reflect this. The Toulmin model of argumentation is applied to practical problems where reasoning is a process of testing ideas. A claim is provided then justified. For an argument to succeed it should provide good justification of a claim. This argumentation model is not as rigorous as those that use logic but provide enough evidence to allow rational acceptance [26]. It is proposed that this more natural description of argumentation can be identified in text and used to determine a structure for that content to make it easy to navigate the conversations in user generated content.

In order to add argument structure to user generated content the format of that structure needs to be defined. Once a structure is determined the text can then be analysed to identify if this structure can be extracted. There are many tools that could be used to support argument analysis directly or extend the analysis and provide further information about the extracted discussion. These are discussed below.

2.1 Data Structures

The aim of structuring data is to provide a basic overview of the data that allows users to more easily understand it. When this content contains a discussion or argument the best way to structure the data is to map it to an argument structure. This allows the user to see the main points of the discussion. The claims and the evidence associated with those claims give the user an indication of where the argument is strong and where it is weak. The points where the claims have weak evidence suggest the most likely places for the evolution of the argument.

Much of the work in argumentation structure comes from the education domain where students map arguments in certain areas. Users discuss a given question and provide claims and counter claims and shape this information into a giant map which allows new users to visualise the discussion easily. If this is done manually it can take a very long time. It is estimated that the production of an argument map describing the debate on whether computers think took 7000 hours to complete [8].

Semantic web technologies such as RDF and ontologies are currently used to define the basis for many existing argument systems [22]. They enable feature rich representation and can be used in automatically identifying patterns. The expression of an argument in an ontological structure allows discourse structure and component relationships to be accessible to computation so that the data can be navigated and compared automatically.

Various semantic web models for argumentation are available including; the Argument Interchange Format (AIF) [17], AIF represented as RDF (AIF-RDF) [17], Issue-Based Information Systems (IBIS) RDF [9], an alignment of two ontologies SWAN/SIOC the Semantic Web Applications in Neuromedicine (SWAN) and Semantically-Interlinked Online Communities (SIOC) [14,22]. Although these formats share a similar underlying RDF structure they are not compatible with each other. The AIF-RDF standard may emerge as the standard that is adopted in this domain as it allows the representation of the largest number of argument schemes. The extensive functionality of AIF-RDF also means that users must identify the logical aspects of argumentation, and as this is complex, this may limit the uptake of the system. As there is no single unified ontology as yet it
is difficult to commit to using a single ontological structure. The adoption of a standard would promote interoperability, but at this point there is a reluctance to commit to one, but rather to remain flexible and adapt to the ontologies as needed for display purposes.

The Toulmin model [25] of argumentation can be used to provide a structure for argument that is more flexible than ontologies based on the logical approaches. This flexible approach is based upon natural which will reflect the nature of discussions found in user generated text. The scheme is made up from 6 components:

1. Claim - A conclusion to be evaluated
2. Ground - Evidence and data, the foundation of the claim
3. Warrant - A statement authorising movement from the ground to the claim (to bridge the gap between claim and ground)
4. Backing - Credentials that certify the statement expressed in the warrant (when the warrant itself is not enough / credible)
5. Rebuttal - Recognising the restrictions which may legitimately be applied to the claim
6. Qualifier - Expressing the force of certainty of the claim

The aim of analysing text would be to identify the claims provided and to identify where those claims are justified. For an argument to succeed it should provide good justification of a claim. For this a claim, ground and warrant are always needed but a qualifier, backing and rebuttal are not. The process would analyse the text to initially identify the claim and ground and when these are found, attempt to find the other components listed above.

Non-ontological models such as that described above generally use machine learning to identify data that belongs to categories in classification schemes. Rose et al [20] use a framework to analyse text for argumentative knowledge construction. This framework classifies text into two initial levels of argumentation: micro-level of argumentation, an individual argument consisting of a claim supported by a ground with warrant possibly specified by a qualifier and macro-level of argumentation, argumentation sequences where single arguments are connected to create an argumentation pattern (argument and a counter-argument).

The classification scheme is based upon the framework of Weinberger and Fischer [27]. The Micro-level text is sub-classified into:

1. Simple claim - Statements without provision of grounds that warrant the claim
2. Qualified claim - Claim without provision of grounds, but with qualifier
3. Grounded claim - Claim with the provision of grounds that warrant the claim
4. Grounded and qualified claim - Claim with grounds that warrant the claim and a qualifier
5. Non-argumentative moves - Questions, coordinating moves, and meta-statements on argumentation

The Macro-level is sub-classified as:

1. Argument - statement put forward in favour of a specific proposition
2. Counter argument - an argument opposing a argument
3. Integration (reply) - statement that aims to balance and to advance a preceding argument and counter argument
4. Non-argumentative moves - Questions, coordinating moves, and meta-statements on argumentation

Another approach to identifying argumentation is via discussion analysis, identifying sentences that contain contrasting ideas. A contrasting idea is identified as a sentence that summarises and encapsulates claim and counter claim, it is the questioning of a previously accepted point, the addition of new facts or theories, the identification of a previous flaw or a contrast between two previous points. Discussion analysis can be used to automatically identify sections of text containing interesting or pertinent information.

Contrasting idea identification is used by Sandor and Vondran [21] to identify key sentences for use in highlighting key threads for reviews when pre-reviewing papers. Key sentences are defined as those that describe the main points of a paper, thus allowing a reviewer to evaluate the flow of the ideas within the article. The features of the key sentences are assigned by applying the concept-matching framework. These features are determined by argumentative expressions which comment on the main points of the paper.

De Liddo, Sandor and Buckingham-Shum [11], also use the XIP parser to aid in Contested Collective Intelligence, the contrasting ideas are extracted and used to analyse problems to aid critical thinking by exploring opposing or diverging opinions.

2.2 Classifying Arguments

Machine learning tools have been used to automatically classify arguments [20,28]. Machine learning algorithms require a good set of features that strongly predict the classes and a feature space that is as small as possible to reduce processing time. The following section looks at the different approaches, algorithms and features that have been used to identify argumentation in text. The text is either classified at the sentence level or the comment level dependent on the type of content used and the end result desired.

Rose et al [20] aimed to identify features that can be extracted from the text that are useful in predicting discourse actions. The tool set TagHelper was used this is a corpus analysis environment built on top of the Weka machine learning toolkit. The training data was text segments assigned to one of seven dimensions. Two approaches were considered: a feature based approach identifying text features that generalise well across categories and an algorithmic approach which was intended to develop the ability to learn very subtle distinctions. The algorithms that were tested were Naive Bayes, Support Vector Machines and Decision Trees. Support Vector Machines were found to be the most successful in identifying the micro and macro argument structure. There is an emphasis in this work on the selection of highly predictive features, such as those indicative of grammatical relations or inclusion of unique or interesting words, rather than on the algorithms employed. From
this exploration it can be determined that it is best to use
uni-grams plus punctuation as the set of base features.

The base set of features as described by Rose et al [20]
was extended by Abbott et al [1] to recognising disagree-
ment in online forums, where people can pose a question or
a topic for discussion. The focus was on the recognition of
argument structure by identifying agreement and disagree-
ment. The machine learning toolkit Weka was used with
Naive-Bayes and JRip algorithms. In addition to the base
set of features, several meta-post features were used such as,
poster id and time between posts. Using the meta post fea-
tures in conjunction with n-grams, disagreement prediction
was increased from 63% to 68%. It was found that users
quote each other in their comments, which allows the users
to break down posts from others into individual points of
argument which they can then respond to in isolation. The
meta-post information can be used to access the relationship
between quoted text and new text.

Somasundaran and Wiebe [23,24] found that other specific
cue phrases were useful. Discourse markers that are strongly
associated with pragmatic functions can be used to predict
the class of content and these features can be extracted from
an annotated corpus ahead of time.

In general, it has been shown that it is difficult to beat a
baseline that uses only uni-grams as features, although sim-
ple rules defined over the content can improve the features
and therefore the classification. However, specific features
can be used to identify aspects of argumentation such as
authority claims, disagreements, and classify the sentences
into claims, grounds and qualifiers. These approaches will
be explored to determine whether the categories taken from
the Toulin approach [25] can be identified and extended.

2.3 Additional Tools

In addition to argument identification other aspects of the
discussion that could provide the user cues as to whether
information is relevant and interesting. These may include
identification of the topics, the quality of the content and
using semantic analysis to determine opinion. These exten-
sions are discussed in more detail below.

Topic identification is useful in identifying subtopics within
a discussion and could be used to label the discussions and
sub discussions. TF-IDF can be used to determine how
strongly terms are associated with specific topics [12] there-
fore past discussions can be used to help those newer to the
discussions. Arguments can become cyclic, identifying the
same small set of issues multiple times and never moving
towards a solution. If topic identification is combined with
a time order it could be used to determine if the argument
is progressing and to see if the range of information covered
is increasing.

Semantic analysis can be used to determine the opinions of
the users from the text in the conversation. This could be
used to model a specific user to identify likely opinions or
to model a conversation and determine the movement of the
argument positions over time. Sentiment analysis has been
applied to text in many areas including blog posts, twit-
ter, and other social networking sites. Potthast and Becker
[15] summarised and visualised comments to give a gen-
eral overview of the sentiment contained within Flickr and
YouTube comments and Balasubramanay et al [4] looked at
comment polarity in political blog posts. Topics were disagree-
ified which cause strong reaction within specific communi-
ties. They used sentiment polarity assigned to community
specific models to summarise issues tackled.

3. WORK IN PROGRESS

An investigation into the current approach to argument
analysis in user generated content has been conducted. To
build upon this a initial dataset has been identified and the
possible visualisation of results considered.

3.1 Visualisation

Argumentation mapping and visualisation systems are used
in teaching and learning to promote discourse between learn-
ers. There is a focus on systems that allow users to create
argument maps or semi-automated systems where the users
annotate extracted arguments. Several systems have been
developed that visualise argument structure including Co-
here, Debatograph and Living Vote [22]. It is proposed that
these visualisation systems could be reused and extended or
procedures and processes reused in the visualisation of arg-
uments extracted from user generated text. These systems
will be evaluated to determine the most useful features.

3.2 Data Sets

The initial stages of this work will aim to identify argu-
ments in a test data set and determine which additional
tools are useful. Some first attempts have been made to de-
sign methods for modelling naturalistic argumentation with
specific data resources, supporting filtering and analysis of
content in a discussion.

Twitter is a micro blogging site, where users can post text
in 140 character segments. The text that is posted is there-
fore short and it does not always use standard spelling or
grammar and contains many specific conventions associated
with this medium such as re-tweeting, hashtags and emoti-
cons. The data is noisy and messy and covers a large number
of parallel conversations all occurring at the same time.

Jodi Schneiders blog [10] gives an example of argumenta-
tion structure in a single tweet in twitter:

Difference between cakes and biscuits? When stale, cakes
go hard, biscuits go soft. Hence Jaffa Cakes are cakes. (Was
official EU ruling)

This tweet is an example of a claim, evidence and grounds
in less than 140 characters. Ramage, Dumais and Liebling
[18] and Ritter, Cherry and Dolan [19] have analysed twitter
to categorise conversation and to identify specific dialogue
acts using Latent Dirichlet Allocation. They both confirm
that while twitter has very specific language and language
constructions, the conversations conducted within this do-
main can be analysed in a conventional way. The data is
freely available, in large volume and is in clearly structured
short conversational pieces.

A data set of hand annotated tweets has been acquired
that describes events surrounding the London Riots in 2011.
This data was originally used to create a visualisation of how
rumours spread through twitter during the London Riots
[16]. Each tweet was annotated with one of the following
codes:

1. Claim without evidence
2. Claim with evidence
3. Counter-claim without evidence
4. Counter-claim with evidence
5. Implicit request for verification
6. Explicit request for verification
7. Comment
8. Other

This data will be used in the next stages of this work. It is intended that machine learning techniques will be used to identify arguments in a test data set and determine which additional tools are useful.

As conversation and arguments within twitter occur within a stream of data therefore the identification of conversations or topics is required. This type of problems has been tackled before in fields like opinion mining of product reviews [6]. Therefore the approach that is taken in this work is inspired by Bal and Saint-Dizier [3]. The steps in the process are:

1. Find the topic (topic detection / clustering)
2. Identify relevant sentences / text spans
3. Classify into argument structure
4. Track opinion (sentiment analysis)

Initial experimentation has been conducted using the hand annotated twitter set. The data is already split into specific topics by human annotators, it was investigated whether this process could be repeated using an unsupervised machine learning technique. The Natural Language Tool Kit (NLTK) was used with the K-means algorithm implementation [5]. The features used were the most popular unigrams and bi-grams (excluding a stop list of common terms). Initial evaluation has show that the topic can correctly be identified much of the time (the minimum score was a Rand Index of 0.89).

The next step in the process is identify the text spans and classify the data into an argument structure. The approach of Rose et al. (discussed in section 2) will be re-implemented. The techniques will then be extended to analyse data from other user generated comment systems. The aim is to locate a dataset based on user added comments on academic literature.

4. ACKNOWLEDGMENTS

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5. REFERENCES


[16] Procter, Rob, Farida Vis, and Alexander Voss. Riot Rumours: How Misinformation Spread on Twitter


