Understanding Cultural Conflicts using Metaphors and Sociolinguistic Measures of Influence

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Abstract

In this article, we outline a novel approach to the automated analysis of cross-cultural conflicts through the discovery and classification of the metaphors used by the protagonist parties involved in the conflict. We demonstrate the feasibility of this approach on a prototypical conflict surrounding the appropriate management and oversight of gun-ownership in the United States. In addition, we present a way of incorporating sociolinguistic measures of influence in discourse to draw further insights from complex data. The results presented in this article should be considered as illustrative of the types of analyses that can be obtained using our methodology; however, no attempt was made to rigorously validate the specific findings reported here. We address open issues such as how our approach could be generalized to analyze cross-cultural conflicts around the world.

1 Introduction

All discourse is a means to convey ideas, fulfill goals and possibly attempt to persuade the listener (Perloff, 2014). Metaphors, which are mapping systems that allow the semantics of a familiar Source domain to be applied to a Target domain so that new frameworks of reasoning can emerge in the Target domain, are pervasive in discourse. Metaphorically rich language is considered highly influential. Persuasion and influence literature (Soppory and Dillard, 2002) indicates messages containing metaphorical language produce somewhat greater attitude change than messages that do not. Metaphors embody a number of elements of persuasive language, including concreteness and imageability (Strzalkowski et al., 2013, Broadwell

et al., 2013, Charteris-Black, 2005). Using this line of investigation, we aim to understand the motivations of a group or of a political faction through their discourse, as part of the answer to such questions as: What are the key differences in protagonists' positions? How extensive is a protagonists' influence? Who dominates the discourse? Where is the core of the groups' support?

Our goal is to provide a basis for the analysis of cross-cultural conflicts by viewing the conflict as an ongoing debate or a "dialogue" between protagonists or participants.

In this interpretation, each major protagonist position becomes a "speaker" and the articles, postings, and commentaries published by media outlets representing that position become "utterances" in a debate. The targets (i.e. main concepts) of the conflict are those concepts that align with the main topics (we shall call them meso-topics) of the debate. Protagonists' positions in the conflict are derived from their language use when talking about these meso-topics, particularly the metaphorical language. The relationships between the protagonist positions are determined based on sociolinguistic features of their "utterances", particularly topic control, disagreement, argument diversity, and topical positioning. These and other features allow us to isolate "subgroups" or factions of like-minded individuals, including those that are more extreme (farther apart) and those that are moderate (closer to a "center"). In addition, we look for indicators of influence these groups exert upon each other as well as upon their other audiences (broader public, lawmakers, policy makers, etc.) We thus aim to bring together two emerging technologies to bear upon conflict case analysis: automated metaphor extraction, and automated analysis of the sociocultural aspects of language.

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Understanding conflicts in this manner may allow policy-makers facilitate negotiations and discussions across different communities and help bridge contrasting viewpoints and cultural values.

2 Relevant Research

The underlying core of our research is automated, large-scale metaphor extraction. Computational approaches to metaphor to date have yielded only limited scale, often hand-designed systems (Wilks, 1975; Fass, 1991; Carbonell, 1980; Feldman & Narayan, 2004; Shutova & Teufel, 2010; inter alia). Baumer et al. (2010) used semantic role labels and typed dependency parsing in an attempt towards computational metaphor identification. Shutova (2010) employ an unsupervised method of metaphor identification using nouns and verb clustering to automatically impute metaphoricity in a large corpus using an annotated training corpus of metaphors as seeds. Several other similar approaches were reported at the Meta4NLP workshop, e.g., (Mohler et al., 2013; Wilks et al., 2013; Hovy et al., 2013). Strzalkowski et al. (2013) developed a data-driven approach towards the automated extraction of metaphors from text and our approach builds upon their work. The use of metaphor, along with sociocultural aspects of language to understand cross-cultural conflict is novel to our approach. Recent research in computational sociolinguistic has developed methods for automatic assessment of leadership, influence and power in conversation (Broadwell et al., 2012; Shaikh et al., 2012; Strzalkowski et al., 2010) and we draw largely upon this work. Other relevant work includes Nguyen et al. (2013), who look at non-parametric topic modeling as a measure of influence; and Bracewell et al. (2012), who look at a category of social acts to determine measures of leadership; among others. Analysis of positions held by discourse participants has been studied in the realm of political science and computational sociolinguistics (Laver, Benoit & Garry, 2003; Slapin & Proksch, 2008; Lin et al., 2013; Pang & Lee, 2008) and our approach draws parallels from such prior work. Our topical positioning approach is a departure from existing approaches to sentiment analysis (Wiebe, Wilson and Cardie, 2005; Strapparava and Mihalcea, 2008) in looking at a larger context of discourse rather than individual utterances.

3 The Conflict – U.S. Gun Debate

The main hypothesis, and an open research question, is then: can this new technology be effectively applied to understanding of a broad cultural conflict such as may arise in any society where potentially divisive issues exist? To answer this question, we decided to conduct a feasibility study in order to scope out the problem. What we present below is the outcome of this study and possibilities it opened for future research. The actual results of conflict case analysis obtained here are for illustrative purposes only.

To start, we selected a conflict case that is both familiar and has abundance of data available that is easily accessible. The case can be considered as representative both in terms of its overall structure (opposing views, radical and moderate positions, ongoing tension) as well as the debate surrounding it (complexity of language, indirectness, talking about self and the others, etc.). At the same time, its familiarity provided means for immediate assessment of feasibility of the proposed approach: if our subject matter experts could verify the outcome as correct or at least reasonable, it would serve as a point of departure for more rigorous analysis and evaluation of other conflict cases elsewhere in the world.

The cross-cultural conflict we use as an example can be summarized as: "*People disagree about the oversight of guns in the U.S. Some believe that guns and gun safety are the responsibility of individuals; others believe that the Federal Government should manage guns and gun ownership. This contrast in viewpoints has been a source of tension in the US since the colonial era. Although the debate about guns is often thought to be political, its foundation is actually cultural – the proper balance between the rights of the individual citizen and the interests and needs of the majority.*"[1]

The protagonists involved in this conflict are those in favor of individual oversight of guns (INDO for short) and those in favor of Federal Government oversight (GOVTO for short). Given a conflict case such as the above, our goal is to develop methods that will understand and analyze the cultural differences that underlie the conflict and can be ascertained through the use of metaphors by protagonists on either side.

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[1] An excerpt from the Guns Practice Case description.

4 Our Approach

4.1 Data Identification and Collection

Our objective was to identify the metaphors that are used to characterize the Gun Case conflict in the U.S. For extracted metaphors to be useful to an analyst in this or any other conflict case, the metaphors must be assigned to a particular protagonist or viewpoint or "side" of whatever debate or conflict is being explored. Without linkage to a viewpoint, discovered metaphors are not particularly illuminating. When dealing with an unfamiliar culture, an analyst may not be able make such a link. Consequently, the system must provide the link. It is the known position, taken by the spokesperson using the metaphor that provides the connection between metaphor and position or side. A spokesperson can be a particular named person – such as the head of an organization espousing the position (i.e., head of the NRA) – but in fact is more commonly a website maintained by an organization for the purposes of promulgating its views.

The first step is the identification of spokespersons and spokesperson sites on all sides of the opinion spectrum. Websites are more helpful than named people, because they provide a large volume of text that is readily accessible in locations that contain high concentrations of material on the focus topic. This step typically requires input from a cultural/political expert; however, it may be approximated (or pre-structured) using the distance calculation based on the Topical Positioning measure (c.f. Section 6).

In the second step, we roughly array these sites along an opinion spectrum, and particularly discover the *extreme positions* at each end of the spectrum, as well as those sites that represent more moderate positions, if still recognizably on each side. This step also requires input by the cultural/political expert; but it may be approximated by the Topical Positioning computation as in first step above, in cases where cultural expertise cannot be obtained.

Once the websites and their positions on opinion spectrum are determined, the third step is collection of data from sites taking a relatively pure and extreme position at each end of the spectrum, after sites have been checked for any access restrictions. Data collection here means downloading snippets of text – passages of up to five sentences – that

contain certain terms of relevance to the conflict case under investigation. We start with a broad list of terms that may include potential metaphorical targets as well as other relevant terms. Table 1 shows a subset of these terms in the first column for the Gun Case. Other terms (see Figure 1) are folded under these broad categories in Table 1.

The effect of this collection method is that all automatically extracted metaphors can be automatically tagged as representing one extreme position or the other, based on the initial classification of the site by the cultural expert. These are considered to be core metaphors. This material should be reasonably balanced as to numbers of sites on each side. We make an effort to compensate significantly unbalanced dataset with additional collection on underrepresented side.

Step four is data collection from the sites closer to the middle of the opinion spectrum identified in the second step. When this data is processed for metaphors, they are labeled accordingly as "moderate". We note that "moderate" positions in multi-side conflicts may have different interpretations than in a largely binary conflict of Gun Case. In Table 1, the column Total Passages represents the sum total of passages processed from the extreme and moderate websites.

Target	Total Passages
Gun control	23596
Gun violence	8464
Gun right(s)	9472
Gun law	11150
Gun safety	129
2nd Amendment	516
Gun ownership	1147
Gun owners	2359
Total	57841

Table 1. Distribution of collected data across targets in Gun Case debate

For the Gun Case analysis, two rounds of data collection were conducted. The first round was focused on extreme sites on both sides: data were derived from 10 extreme INDO sites and 20 extreme GOVTO. The greater number of sites in favor of more government oversight was necessary because of the lesser volume of text found in these sites on the average. In the second round of data collection, we added sites that represented moder-

ate positions. Ultimately, we collected data from 45 online sites and collected more than 57,000 text passages as seen in Table 1.

4.2 Identifying Meso-Topics and Targets for Metaphor Extraction

The downloaded data is then processed for meso-topics (frequently mentioned and polarized topics) and metaphors.

The process of identifying the key meso-topics (i.e., the main aspects of the conflict case) has been fully automated in the following 3 steps:

1. Locating frequently occurring topics in text: The initial candidates are noun phrases, proper names (of locations, organizations, positions, events, and other phenomena, but less so of specific individuals). These are augmented with co-referential lexical items: pronouns, variants, and synonyms. The process of selection is quite robust but requires some rudimentary processing capability in the target language: part-of-speech tagging, basic anaphor resolution, and a lexicon/thesaurus.

2. Down selecting the frequent topics to a set of 20-30 meso-topics. The two key criteria for selection are length and polarization. Topic "length" is measured by the number of references to it (either direct or indirect) that form "chains" across the "utterances" that are part of the conflict debate. Topic polarization is measured by the proportion of polarized references to a meso-topic, either positive or negative. For example, the terms gun rights and gun safety are both frequently used and polarized in the Gun Case. In order to keep the analysis manageable, we retain only top 20 to 30 meso-topics, based on their chain lengths.

3. Selecting metaphorical targets and assigning them to case aspects. While all meso-topics are important to the case, only some of them will be targets of metaphors. We determine this by probing metaphor extraction for each of the meso-topics and then eliminating those meso-topics that bring back too few metaphors. In the Gun Case, we used 2% cut-off threshold for productive targets (a typical metaphor to literal ratio is approx. 8%).

Figure 1 shows the meso-topics selected for the Gun Case, and the metaphorical targets identified among them (bold face). Targets are grouped by semantic similarity and assigned to case "aspects".

Figure 1. Meso-topics and metaphorical targets identified for the Gun Case

4.3 Extracting Linguistic Metaphors and Building Conceptual Metaphors

Our metaphor extraction system was run over approximately 57 thousand passages collected from the Gun Case protagonists' media outlets, resulting in more than 4000 distinct linguistic metaphors (LMs). These LMs yielded 45 conceptual metaphors (CMs), with 28 CMs on the individual oversight (INDO) side and 17 CMs at the government oversight (GOVTO) side. This uneven split represents the overall data distribution between INDO and GOVTO, reflecting their relative contributions to the Gun Case debate: approximately 70% of contributions (measured in published "utterances") are attributed to the INDO side.

We define the terms LM and CM here: a linguistic metaphor (LM) is an instance of metaphor found in text, for example – "*The roots of gun control are partially about racism*". Here the target is *gun control* and the metaphorical relation is "*roots of*". A prototype source domain for this metaphor could be PLANT, where *gun control* is likened to having properties of a PLANT by the relation *roots of*. A set of linguistic metaphors all pointing to the same source domain, such as PLANT in the above example, would form a conceptual metaphor (CM). The focus of this article is on the use of metaphors towards analyzing a real world conflict scenario. Metaphor extraction is carried out in a data-driven, automated method by our system by using corpus statistics, imageablity and identification of source domains using word vectors to represent source domains. Our work is built upon existing approaches to automated metaphor extraction and source domain mapping (Strzalkowski et al., 2013; Broadwell et al., 2013; Shaikh et al., 2014). Our system extracts linguistic metaphors from text and

Target	INDIVIDUAL OVERSIGHT; Selected CMs/ Total CMs: 28
GUN RIGHTS	ANIMAL (shoot, survive, endanger) BARRIER (push, circumvent, wedge) WAR (battle, victory, jihad) GAME (win, game, champion) A_RIGHT (preserve, lose, violate) CLOTHING (wear, strip, cling) BUILDING (restore, prospect, platform) BUSINESS (sell, expand)
CONTROL OF GUNS	MACHINE (failure of, misfire, defuse) ANIMAL (kill, shoot, evolve) BARRIER (break, ram, hinder) NATURAL_PHYSICAL_FORCE (strong, defy, sweep) WAR (fight, attack, battle) HUMAN_BODY (weak, relax, thrust) BUSINESS (launch, promote) GAME (champion, bandwagon, loser) CLOTHING (tighten, loosen)
GUN VIOLENCE	DISEASE (epidemic, scourge, plague) CRIME (victim, rampant) ACCIDENT (die from, horrific, injury) WAR (battle, fight, escalate)

Table 2. Conceptual Metaphors used by protagonists on the INDO side

Target	GOVERNMENT OVERSIGHT; Selected CMs/Total CMs: 17
GUN RIGHTS	WAR (battle, attack, victory) BUILDING (restore, preserve)
CONTROL OF GUNS	BARRIER (push) NATURAL_PHYSICAL_FORCE (strong) WAR (battle, attack, defend) HUMAN_BODY (strong, tough) CLOTHING (tighten, loosen) PROTECTION (violate, protection)
GUN VIOLENCE	DISEASE (epidemic, survivor) CRIME (victim, perpetrator, rampant) ACCIDENT (tragic, die, gruesome) WAR (fight, carnage, threat) NATURAL_PHYSICAL_FORCE (devastating, brunt of)

Table 3. Conceptual Metaphors used by protagonists on the GOVTO side

automatically groups them together to form conceptual metaphors. The source domains that we refer to in this article are a set of 67 categories that are frequently encountered in metaphorical data.

Tables 2 and 3 below show the overall distribution of CMs found on each side of the debate. Selected representative lexical items associated with each CM are shown in parentheses. Similar tables can be drawn for extreme and moderate positions separately in the debate.

We can now automatically label the metaphors across given positions, extreme or moderate, on each side of the debate. The process of labeling the

metaphors then leads to analytic insights into the data, which we shall present in the next section.

5 Preliminary Insights using Metaphorical Data

We report three observations based on automated processing of relevant text sources for presence of metaphorical language used by each protagonist. We should stress here that these are only tentative results that serve as indication of the types of analyses that may be achievable. Rigorous validation is required to confirm these findings; however, it was not our objective of this feasibility study.

5.1 Contrasting Narratives: DISEASE vs. WAR

Both sides of the debate use metaphorical language indicative of their stances on the Gun Case issue. These metaphors invoke a variety of source domains from which we can infer their attitudes toward the issue. Among all source domains invoked by each side, two are predominant:
1. DISEASE is invoked in 21% of all metaphors used by GOVTO
2. WAR is invoked in 20% of all metaphors used by INDO

To determine predominant Conceptual Metaphors for each protagonist (21% and 20% referred above), we rank order the Source Domains (SDs) for each side by number of LMs that use each SD. In Table 4, we show the predominant conceptual metaphors used for key targets by each protagonist.

Target	Government oversight (GOVTO; Anti-gun)	Individual oversight (INDO; Pro-gun)
Gun rights	BUILDING (*)	WAR
Control of guns	NAT_PHYSICAL FORCE	WAR BARRIER
Gun violence	CRIME DISEASE	DISEASE

Table 4. The most representative CMs on both sides of the Gun Debate, by key Targets. Font size indicates relative frequency for top CMs for each target.

WAR and DISEASE/CRIME dominate; however, we note also that the majority of metaphors on GOVTO side come in fact from *gun violence* topic, while on the INDO side the majority comes from the *gun rights* topic. Further breakdown of top

source domains for the gun debate targets is elaborated as follows: NATURAL PHYSICAL FORCE, DISEASE and CRIME all seem to contribute towards a cohesive narrative on the GOVTO side, which views the gun issue as an uncontrollable, external, negative force. BARRIER and WAR on INDO side may suggest an overarching narrative of active struggle and overcoming of obstacles.

This resolution of narratives for each side in a conflict is a significant key insight that can be derived from gathered data. Recognizing the underlying narrative in a conflict for any given side can provide ways of resolving conflict by facilitating dialogue that can bridge such differences.

5.2 Sociolinguistic indicators: INDO dominates debate

The INDO side contributes approximately 70% of all content in the Gun Case debate. This proportion does not change substantially even after a deliberate oversampling of data from GOVTO websites. The absolute number of metaphors supplied by INDO is substantially greater than the number produced by GOVTO sites. In addition to contributing the most content and the largest number of metaphors (Figure 4), the INDO side dominates the Gun Case debate according to two key sociolinguistic measures (Broadwell et al., 2012):

1. Showing greater Argument Diversity, which correlates with greater influence. Argument diversity is a sociolinguistic measure manifested in metaphor use by: (a) employment of a larger number of source domains in their metaphors; and (b) Employment of more varied metaphors using distinct relations

2. Using action-oriented language, i.e., the relations in metaphors evoke action for change rather than describing the status quo.

To gather evidence for this insight, we explored the sociocultural indicators of influence exhibited by the INDO side. Figure 4 shows the INDO using significantly more metaphors in most domains, except for DISEASE, CRIME, and NAT-PHYS-FORCE, which are parts of the GOVTO core narrative. Figure 5 further shows that INDO uses more varied relations to evoke these domains, even those SDs used predominantly by GOVTO.

Figure 6 illustrates INDO using more action-oriented language in their metaphors. The two pie charts represent the proportion of lexical items

used in LMs that are of the "taking action" type (primarily verbs describing events, such as "*attack*") vs. the "passively observe" (primarily nouns and adjectives, such as "*devastating*").
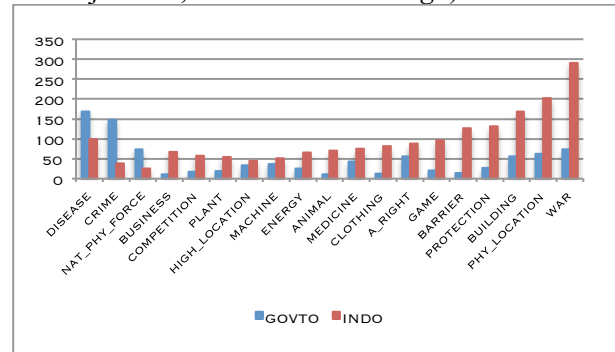
Figure 4. The INDO side (red bars) dominates debate with use of more LMs overall. Here we show those source domains that are used at least 2% of the time overall by both sides and the count of LMs for those Source Domains. Y-axis represents count of metaphors.
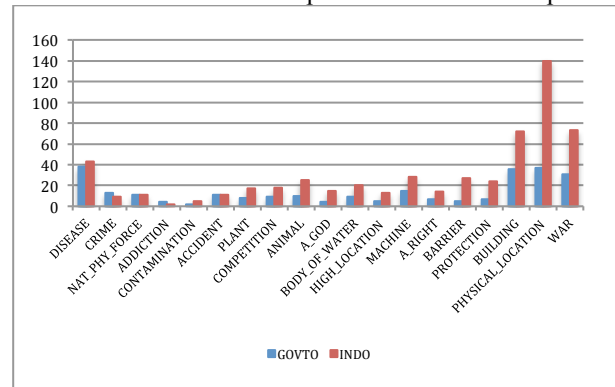
Figure 5. The INDO side dominates debate with richer vocabulary suggesting greater influence. Here we show those source domains that are used at least 2% of the time overall by both sides and the <u>count</u> of distinct relations in the LMs by each protagonist. Y-axis represents count of metaphors.
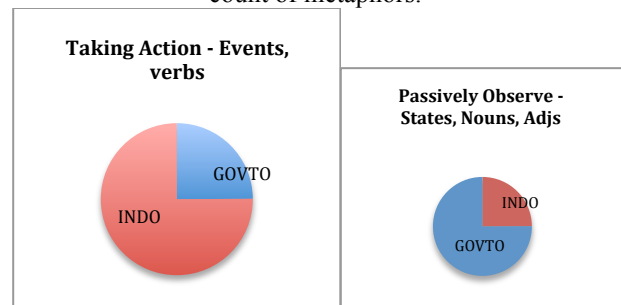
Figure 6. The INDO side dominates debate with use of more action-oriented language. Size of pie chart represents the proportion of metaphors in the source role categories. The "Taking Action" type of metaphors is greater in proportion than "Passively Observe" type of metaphors.

5.3 Topical positioning: INDO occupies the center ground in debate

We wish to calculate the relative positions of protagonists in a debate and to estimate a distance between these positions. We have created a sociolinguistic method of computing those distances using a method called Topical Positioning (Lin et al., 2013). In this section, we shall explain how we arrive at those distances using metaphorical data and give details about the Topical Positioning Method in Section 6.

In order to calculate the positions of extreme and moderate protagonists on each side of the debate, we create a heat-map matrix of metaphor usage for each position. Each matrix represents the numbers of metaphors and Source Domains applied to each key target concept in the debate. Distances between matrices are calculated using cosine measure in multidimensional spaces. Figure 7 shows fragments of heat maps for the extreme GOVTO and INDO positions.

Figure 8. INDO side occupies center ground in the gun debate. We represent each protagonist position on a relative distance "scale"

Using this method, we find that the extreme proponents of the INDO and GOVTO sides are far apart, approximately 0.55 of the maximum theoretical distance of 1.0. Using the same measures, the distance between the INDO moderate position and both INDO and GOVTO extremes is approximately half of the above, or 0.27. This places the INDO moderate position in the center of the spectrum of positions between the two extremes. On the other hand, the language used by the GOVTO moderate position places them closer to the GOVTO extreme. This finding is illustrated in Figure 8.
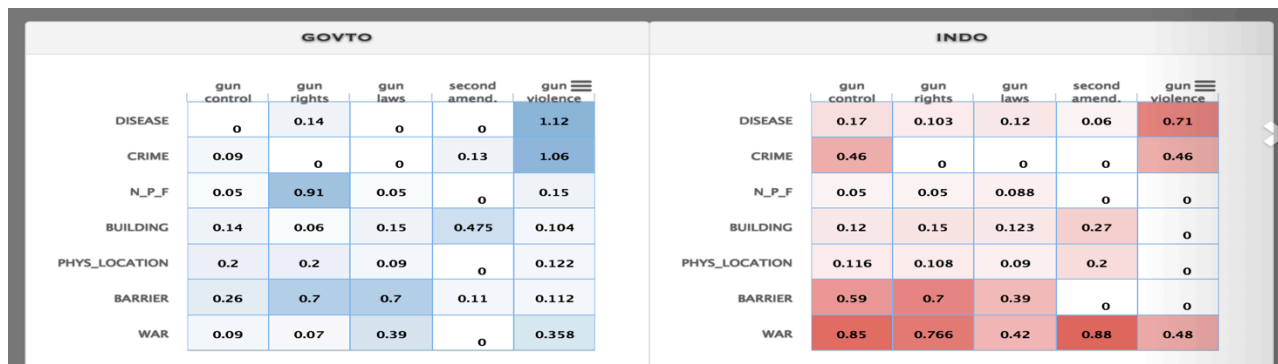
In this section we presented three observations

Figure 7. Protagonist matrices shown as heat maps. The intensity of color shows greater proportion of LMs for particular Target-Source mappings. We compute cosine distances between these matrices to determine relative positions of protagonists.

Each $N \times M$ matrix provides the representation of a protagonist position in a debate through their use of metaphors where N represents the number of metaphorical Targets (TCs) in a debate, while M represents the number of source domains (SDs) used in the analysis. Values in each cell represent an average strength score for $TC \rightarrow SD$ mappings found in the data collected from this protagonist media outlets (Shaikh et al., 2014). Empty cells are values below a preset threshold, replaced by 0s. To calculate distances we use a cosine metric; however, other distance measures may also be applicable.
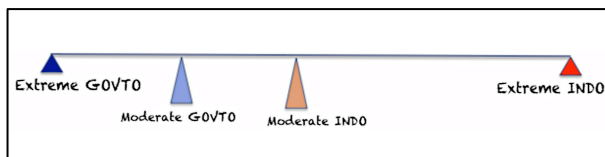
that emerged, from the snapshot of data we collected on this prototypical case and by running automated tools of metaphor and sociolinguistic analyses on the data. These results were confirmed by subject matter experts, who were intimately familiar with the issue. We note that such verification does not constitute a rigorous validation of our findings, the goal of this paper is to present a possible solution and path towards generalizability, validation is a separate issue that we may explore as future work. The selection of a familiar cross-cultural conflict allowed us to propose and test viable solutions that can be adapted to work on previously unknown conflicts.

6 Topical Positioning

While the two sides of the debate use different metaphors to convey their views of the gun issue, it is not immediately clear just how far apart these positions are, and thus how strong or intractable the conflict really is. One possible way to compute the distance between protagonists is to use the method of Topical Positioning (Lin et al., 2013)

In discourse analysis, *Topical Positioning* is defined as the attitude a speaker (our protagonist) has on main topics (meso-topics) of discussion. Speakers in a dialogue, when discussing issues, especially ones with some controversy, will establish their attitude on a topic, classified as for, against, or neutral/undecided.

To establish topical positioning, we first identify meso-topics that are present in a debate, as discussed in Section 4.1. We then distinguish multiple forms in which polarization or valuation is applied to meso-topics in protagonists' utterances such as through express advocacy or disadvocacy or via supporting or dissenting information, and express agreement or disagreement with a polarized statement made in a statement by the same or another protagonist. We create Topical Positioning Vectors representing each protagonist. Table 5 shows a fragment of positional vectors for extreme GOVTO and INDO positions for five meso-topics. In these vectors, value in each cell represents a prevailing combined polarity and intensity towards a meso-topic. We note that meso-topics form a superset of metaphorical targets as explained earlier.

M-topics	Hand guns	firearms	gun owners	gun control	gun rights
INDO	4	5	5	0	5
GOVTO	0	-1	0	5	-1

Table 5. Topical Positioning vectors for extreme GOVTO and INDO positions in the gun debate

Topical Positioning vectors can now be used to calculate distance between protagonists, using standard cosine measure. We used this method to compute 4-ways distances in the Gun Case: between the extreme positions on each side; between the moderate and extreme positions within each side; as well as between moderates and extremes across the sides and compared the distances so obtained to those obtained from metaphorical matrices (Section 5.3). We note that both methods yielded essentially identical results. The distance between extreme positions on INDO and GOVTO side appears to be very large, varying between 0.55 and 0.58. The distances between moderates and between moderates and extremes are appropriately smaller (~0.27). The distance between moderate and extreme INDO places the former in the center between the two extremes. This result is confirmed by the smaller than expected distance between moderate and extreme GOVTO. This may suggest that moderate INDO (thus, the INDO side) dominates the debate by effectively occupying its center.

7 Discussion and Open Issues

In this paper, we presented a preliminary yet innovative approach towards the understanding of cultural conflict through the use of metaphors and sociolinguistic measures of influence. Our approach was illustrated on the analysis on a prototypical case centered on the U.S Gun debate. By casting the problem as an analysis of discourse, or debate between protagonists, we gain significant benefits – we can use established social science methods to draw potentially illuminating and non-trivial insights from otherwise very complex and often conflicted data. We believe that the approach presented here can be generalized to other types of conflict by following the steps detailed in Section 4. It is possible that issues with multiple, clearly distinct sides all aimed at clearly distinguishable solutions to a general issue may need to be dealt with as clusters or will need to be broken down into multiple two- or three-sided conflicts, depending upon the precise goals to be achieved.

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