

# Corpus for Modeling User Interactions in Online Persuasive Discussions

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## Abstract

Persuasions are common in online arguments such as discussion forums. To analyze persuasive strategies, it is important to understand how individuals construct posts and comments based on the semantics of the argumentative components. In addition to understanding how we construct arguments, understanding how a user post interacts with other posts (i.e., argumentative inter-post relation) still remains a challenge. Therefore, in this study, we developed a novel annotation scheme and corpus that capture both user-generated inner-post arguments and inter-post relations between users in ChangeMyView, a persuasive forum. Our corpus consists of arguments with 4612 elementary units (EUs) (i.e., propositions), 2713 EU-to-EU argumentative relations, and 605 inter-post argumentative relations in 115 threads. We analyzed the annotated corpus to identify the characteristics of online persuasive arguments, and the results revealed persuasive documents have more claims than non-persuasive ones and different interaction patterns among persuasive and non-persuasive documents. Our corpus can be used as a resource for analyzing persuasiveness and training an argument mining system to identify and extract argument structures. The annotated corpus and annotation guidelines have been made publicly available.

**Keywords:** Argument Mining, Argument Schemes, ChangeMyView

## 1. Introduction

In recent years, there have been advances in argument mining, a research field that analyzes argumentation or argumentative structures in a text using natural language processing. Several studies have proposed argument mining schemes (Stab and Gurevych, 2014; Habernal and Gurevych, 2016b), providing datasets with human annotations. The majority of the studies focused mainly on the identification and classification of argumentative components (e.g., *claim* and *premise*) and the argumentative relations between the components (e.g., *support* and *attack*) in argumentative documents (Palau and Moens, 2009; Walton, 2012; Stab and Gurevych, 2017; Habernal and Gurevych, 2017; Boltužić and Šnajder, 2016).

Several recent studies have also focused on the analysis of argumentation in persuasions or debates (Habernal and Gurevych, 2016b; Tan et al., 2016; Habernal and Gurevych, 2016a; Persing and Ng, 2017; Musi and Aakhus, 2018; Hidey and McKeown, 2018; Ji et al., 2018; Durmus and Cardie, 2019; Gleize et al., 2019; Hidey et al., 2017). These studies aim to reveal how individuals provide arguments to persuade an opponent. In addition, they aim to predict an opponent’s strategy and identify the attributes that make arguments convincing. For example, Tan et al. (2016) proposed an epoch-making task to predict which arguments were more persuasive in an online persuasive forum. Hidey et al. (2017) provided a novel corpus on the Tan et al. (2016) to reveal persuasive interactions. However, with the exception of some studies, such as (Chakrabarty et al., 2019; Ghosh et al., 2014), there are insufficient resources and annotation schemes for analyzing persuasive interactions. Motivated by the demand for interaction analysis in online persuasive discussions, in this study we developed a novel corpus for persuasive discussions. To investigate the interaction between user posts, we proposed a novel annotation scheme that captures argument structures in a post and inter-post interactions on the basis of ChangeMyView (Tan et al., 2016). Figure 1 presents an exam-

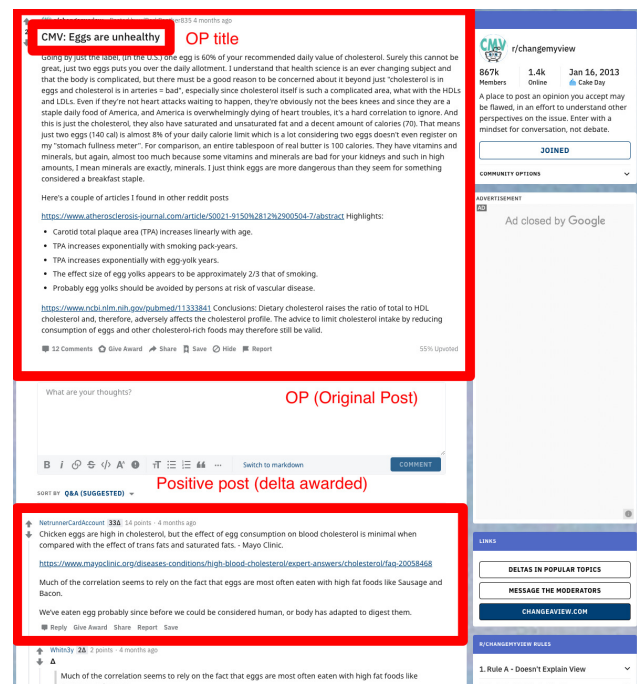


Figure 1: In ChangeMyView, original post (OP) users submit a claim as the OP title, providing the rationale for the claim throughout their posts. A positive post is a winning argument in which the OP user was persuaded by the argument. Note that we only use data for cases where the OP user is persuaded (Tan et al., 2016).

ple thread in ChangeMyView (<https://www.reddit.com/r/changemyview/>). ChangeMyView is a subreddit in which users post an opinion (called a *view*) in an OP title (e.g., “*CMV: Eggs are unhealthy*” in Figure 1) and rationale for the opinion. Challengers other than the OP user attempt to change the OP user’s *view* through their comments, and a positive post refers to a post that changes the OP user’s view.

To capture the interaction between user posts in the online



Figure 2: Example of proposed annotation in ChangeMyView, in which the OP title is considered a Major Claim (colored in gray).

persuasive discussion, we defined an annotation scheme that comprises five types of elementary units (EUs), two types of inner-post relations (INNERRELS), and two types of inter-post relations (INTERRELS). Figure 2 presents an example of the proposed annotation in ChangeMyView, in which a positive post is a post that is successful at changing the OP user’s view, and a negative post is a post that is not successful. In the example, each post (OP, positive, negative) is annotated with EUs, their INNERRELS, and INTERRELS. Each EU represents argumentative components common in online discussions, such as Fact, Testimony, Value, Policy, and Rhetorical Statement. INNERREL represents the support/attack relation for the reasoning between EUs, while INTERREL represents the relation between argument structures in an OP and a reply post. This annotation makes it possible to capture the interaction between user posts.

The contributions of this study are as follows:

- We proposed an annotation scheme that captures EUs, INNERRELS between EUs, and INTERRELS.
- We annotated 4612 EUs, 2713 INNERRELS, and 605 INTERRELS in 115 threads. In addition, we computed the inter-annotator agreement (IAA) using Krippendorff’s alpha, resulting in reasonable agreement of  $\alpha_{EU} = 0.677$ ,  $\alpha_{InnerRel} = 0.532$ , and  $\alpha_{InterRel} = 0.579$ .
- We investigated the properties of the interactions in OP-positive and OP-negative relations, and captured the patterns in these interactions.

The remainder of this paper is organized as follows. In Section 2., we describe related research and datasets. In Section

3., we provide an overview of our annotation scheme and annotation results. In Section 4., we analyze the annotated corpus statistically and linguistically, and in Section 5., we present conclusions and ideas for future work.

The annotation guidelines and annotated dataset are publicly available<sup>1</sup>.

## 2. Related Work

Recent studies on argument mining constructed datasets by proposing argument schemes (Stab and Gurevych, 2017; Habernal and Gurevych, 2017; Park and Cardie, 2018). Stab and Gurevych (2017) and Persing and Ng (2016) provided argumentative essay datasets that were annotated based on the argument schemes, including *Claim*, *Major Claim*, and *Premise*, and their *support/attack* relations. Habernal and Gurevych (2017) proposed an argument model, including *Claim*, *Data*, *Warrant*, *Backing*, *Qualifier*, and *Rebuttal* for analyzing web discourse. Park and Cardie (2018) extended the argument model of (Hollihan and Baaske, 2005) to capture the semantics of the argumentative component and their support relations. In addition, they created the e-rulemaking dataset. Al Khatib et al. (2016) also focused on the semantics of argumentation strategies in news editorials.

In addition, many studies examined persuasive documents and analyzed the properties of persuasive discussion (Tan et al., 2016; Habernal and Gurevych, 2016a; Musi and Aakhus, 2018; Hidey et al., 2017; Chakrabarty et al., 2019). Tan et al. (2016) and Habernal and Gurevych (2016b) investigated the lexical features of persuasive documents by

<sup>1</sup> [http://katfujilab.tuat.ac.jp/nlp\\_datasets/](http://katfujilab.tuat.ac.jp/nlp_datasets/)

proposing a novel dataset. Chakrabarty et al. (2019) proposed a dataset by developing a scheme of micro-level and macro-level annotation from a dataset in a previous study (Hidey et al., 2017). This scheme captured inner- and inter-post relations. Egawa et al. (2019) proposed an annotation scheme that expanded the scheme of Park and Cardie (2018), and which captured the semantics of argumentative components and their relations. Morio et al. (2019) analyzed the annotation scheme of (Egawa et al., 2019) by proposing baseline neural models that identified the EU boundary and type. These datasets, however, were insufficient for analyzing the semantics of argument interactions between users because they failed to achieve macro-level annotation and capture semantics. Therefore, in this study we focus on creating a dataset that captures the semantics of argumentative components and their inner- and inter-post relations.

### 3. Corpus Annotation

#### 3.1. Data Source

To develop a corpus for online persuasive discussions, we used a dataset from *ChangeMyView* (Tan et al., 2016), which is an online discussion forum in which users initiate discussion by posting their *View* and their reasoning behind the *View* as an OP. Then, challengers attempt to change the OP's *View* by presenting different perspectives on the *View*. If the challengers are successful, the OP user provides a Delta Point ( $\Delta$ ) to the challenger who successfully changes his/her view. Tan et al. (2016) released a dataset for *persuasion prediction* to predict persuasive arguments. Each thread in the dataset comprised an OP, positive post (which won a  $\Delta$ ), and negative post (which was not awarded).

In this study, we developed a corpus on the basis of a previously annotated corpus (Egawa et al., 2019). In (Egawa et al., 2019), the authors annotated 115 threads from the *ChangeMyView* dataset (Tan et al., 2016), providing segmentation and classification of EUs and argumentative relation identifications between EUs in a post. In this study, we annotated argumentative interactions between users using a novel scheme.

#### 3.2. Annotation Scheme

We defined five types of EUs, two types of INNERRELS between units, and two types of INTERRELS between posts. This annotation scheme captures the semantics of the argumentative components and their inner-post relations and inter-post relations. Consequently, we can analyze how arguments are built to persuade others.

##### 3.2.1. Elementary Units

We extended the scheme of Park and Cardie (2018) to classify the features of argumentative components in online persuasive discussions, such as describing personal experiences, facts, and rhetorics. There are five types of EUs, which are defined as follows:

**Fact:** This is a proposition describing objective facts as perceived without any distortion by personal feelings, prejudices, or interpretations. Unlike Testimony, this proposition can be verified with objective evidence; therefore, it represents the evidential facts for persuasion. Examples of Fact are as follows:

- This academic study of university students shows similar rates of victimization between men and women
- they did exactly this in the U.K. about thirty or so years ago
- From this PDF [link], in 2012, there were 4516 reported cases of pertussis in babies under 1 year of age

**Testimony:** This is an objective proposition related to the author's personal state or experience. This proposition characterizes how users utilize their experience for persuasion. Examples of Testimony are as follows:

- I've heard suggestions of an exorbitant tax on ammunition
- I don't drink very often - maybe once a month
- I've been depressed for a long time

**Value:** This is a proposition that refers to subjective value judgments without providing a statement on what should be done. This proposition is similar to an opinion. Examples of Value are as follows:

- it's not something all that gender specific
- safe spaces, where only those of a certain group are allowed to speak, are more often harmful than helpful
- This just isn't the case

**Policy:** This is a proposition that offers a specific course of action to be taken or what should be done. It typically contains modal verbs, such as *should*, or imperative forms. Examples of Policy are as follows:

- All firearms must be traceable
- we should not permanently punish people for mistakes they made in the past
- Vaccines should be administered after one year of age, at least

**Rhetorical Statement:** This unit implicitly states the subjective value judgment by expressing figurative phrases, emotions, or rhetorical questions. Therefore, it can be considered a subset of Value<sup>2</sup>. Examples of Rhetorical Statement are as follows:

- What does that mean?
- That's human nature!
- if one is paying equal fees to all other students why is one not allowed equal access and how is this a good thing?

<sup>2</sup> Unlike Value, we allow a Rhetorical Statement to be an incomplete sentence because it is usually expressed implicitly.

Post type	#Fact	#Testimony	#Value	#Policy	#RS	#Total	#Support	#Attack	#Total
OP	52	134	914	44	157	1301	864	128	992
Positive	127	134	1338	55	327	1981	924	108	1032
Negative	78	86	882	41	243	1330	595	94	689

Table 1: Annotation results of EUs and INNERRELS

Interaction type	#Support	#Attack	#Total
OP-Positive	36	301	337
OP-Negative	25	243	268

Table 2: Annotation results of INTERRELS

### 3.2.2. Inner-post Relations

INNERREL represents a relation between EUs in a post; for example, X (premise) is the positive/negative reasoning for Y (claim). There are two types of INNERRELS. Because we modeled arguments with a one-claim approach (Stab and Gurevych, 2017) that considers an argument as the pairing of a single claim and a set of premises that justify the claim, INNERREL builds an argument structural tree. The two types of INNERREL are defined as follows:

**Support:** An EU X has a support relation to another EU Y if X provides positive reasoning for Y. It is typically linked by connectives such as *therefore*. Examples of a support relation are as follows:

- **X:** No change in service, yet the cost of water and sewer service has literally tripled since the change (Testimony)  
**Y:** these are essential to public well-being and should not be monopolized by a for-profit corporation (Policy)
- **X:** Downs syndrome is a mutation that causes sterility (Fact)  
**Y:** people with downs syndrome don't have children, and there is no genetic cause for it (Value)

**Attack:** An EU X has an attack relation to another EU Y if X provides negative reasoning for Y. It is typically linked by connectives such as *however*. Examples of an attack relation are as follows:

- **X:** Young men are the most likely demographic to get into an accident (Value)  
**Y:** that does not warrant discriminating against every individual in the group (Value)
- **X:** They supported me for a long time (Testimony)  
**Y:** when I look at them objectively, they are average human beings (Value)

### 3.2.3. Inter-post Relations

INTERREL represents a relation between the claim of an argument in a reply post and certain EUs in the OP. Therefore, by annotating INTERRELS in addition to EU and INNERRELS, we can analyze the interaction of EUs/arguments between an OP and a reply post. There are two types of INTERRELS, which are defined as follows:

**Support:** Claim X in a reply post has a support relation to an EU Y in the OP if X is a concession to Y. Examples of a support relation are as follows:

- **X:** As a firearm owner, your responsibility to secure it is exactly that (Value)  
**Y:** If a firearm is used in a crime or is found in the wrong hands, the weapon's registered owner must be held to account (Policy)
- **X:** I agree with a majority of what you said (Value)  
**Y:** I believe that modern, mass media is biased, corrupt, and is only concerned with getting views. CMV (Major Claim)

**Attack:** Claim X in a reply post has an attack relation to an EU Y in the OP if X is a rebuttal to Y. Examples of attack relation are as follows:

- **X:** responsible parents don't need a ban in order to not bother other people, and inconsiderate assholes will always be inconsiderate regardless of what you ban (Value)  
**Y:** I believe people should not be allowed to bring babies in a movie theater except if it's a special "everybody can bring their babies" showing/theater. CMV (Major Claim)
- **X:** alcohol isn't really something to be fearful of (Value)  
**Y:** it resulted in me being fearful of smoking, any drugs, and alcohol (Testimony)

### 3.3. Annotation Process

The annotation task is divided into three steps: (1) segmentation and classification of EUs, (2) INNERREL identification, and (3) INTERREL identification.

This study is an extended task of Egawa et al. (2019), in which the authors annotated EU types and INNERRELS between units. In this study, we annotate INTERRELS to capture post-to-post interaction.

We recruited 19 annotators, and each annotator was asked to read the guideline before actual annotation and attend several training meetings.

In the actual annotation, three annotators independently annotated 50 threads, while the remaining 65 threads were annotated by expert annotators. In the 50 threads, a gold standard was established by using a majority vote to merge the three annotation results.

### 3.4. Annotation Result

Tables 1 and 2 present an overview of the annotated corpus. Our corpus contains 4612 EUs, 2713 INNERRELS, and 605 INTERRELS in 115 threads. The table indicates that most of the EUs are of type Value, which provides a subjective opinion, and most of the INNERRELS are of type support, which logically reinforces the argument. Furthermore, approximately 90% of the INTERRELS are attack relations. This is likely due to the characteristics of a persuasion forum, in

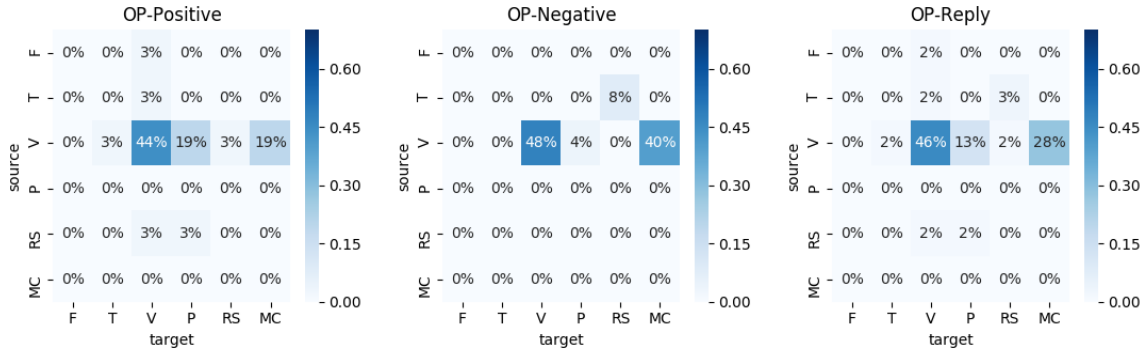


Figure 3: Transition matrix of support relation.

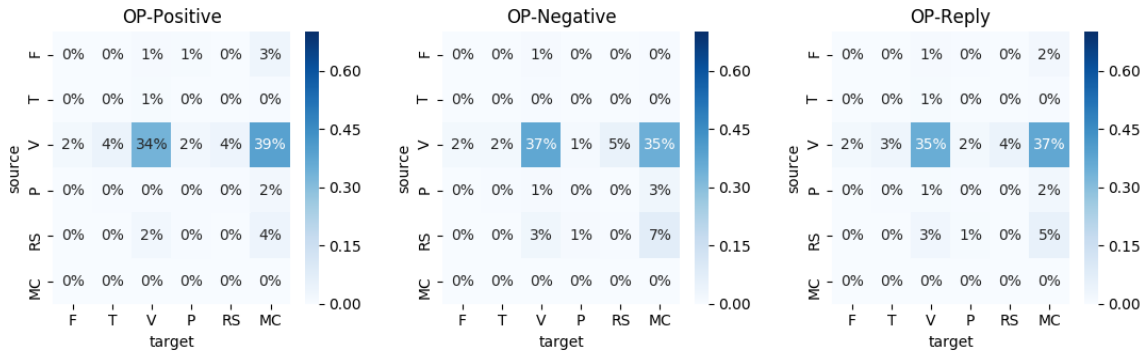


Figure 4: Transition matrix of attack relation.

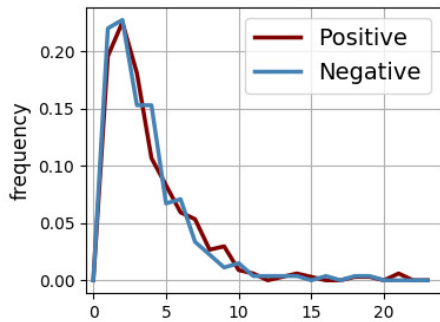


Figure 5: Histogram of the number of EUs in an argument.

which individuals tend to make rebuttals to change other’s opinion.

### 3.4.1. Inter-Annotator Agreement

We computed an inter-annotator agreement (IAA) using Krippendorff’s  $\alpha$  (Krippendorff, 2004). The result of the IAA was  $\alpha_{EU} = 0.677$ ,  $\alpha_{InnerRel} = 0.532$ , and  $\alpha_{InterRel} = 0.579$ . The IAA results of EUs and INNERRELS were higher than in a previous study (Park and Cardie, 2018) in which EUs and their relations were annotated (EUs = 0.648 and inner-post relations = 0.441). Chakrabarty et al. (2019) reported the resulting IAA is  $\alpha = 0.61$  for relation presence and 0.63 for relation types, which is higher than our results due to the difference of annotation scheme<sup>3</sup>. We consider that the high agreement of INTERRELS is due to the nature of a post in ChangeMyView. In ChangeMyView, we

<sup>3</sup> Our annotation identified relation presence and types at the same time

consider an OP to be generally classified into two types: (i) a case that makes a claim based on a certain perspective, and (ii) a case that makes a claim based on some perspectives. In the case of (i), a reply post tends to make a rebuttal to the Major Claim directly, while in the case of (ii), a reply post tends to make a rebuttal to each perspective and cites several sentences that represent a certain perspective. This is why we consider that the agreement of INTERRELS is high.

Most of the disagreement in INTERRELS annotation is caused by semantic similarity. For example, when the Major Claim is “While I agree with vegetarianism, I still eat meat because I don’t think it will make a difference to the meat industry whether or not one person eats meat.”, the OP user finally makes a claim as a statement of the View using rhetorics, such as “Why should I be a vegetarian then?”. In this case, these two EUs represent the same meaning: “I do not think I need to be a vegetarian”.

## 4. Corpus Analysis

To examine the properties of persuasive discussion, we analyzed the INTERRELS considering EUs and INNERRELS.

### 4.1. Number of interactions

Table 2 presents the number of INTERRELS in each post. The results indicate that a positive post tends to make claims more than a negative post (interactions per post in positive = 2.93 and negative = 2.33). In addition, this is consistent with the previous analysis of persuasiveness (Tan et al., 2016), such as the number of sentences and paragraphs is more in a positive post than in a negative post.

## 4.2. Semantic types of Claim

We investigated how a reply post interacts with the OP. Figures 3 and 4 illustrate the annotation results of INTERRELS in each type of relation. Here, *source* represents the type of claim in a reply post, and *target* represents the type of supported/attacked EU in the OP. In a support relation, a positive post tends to make a concession to the Policy of the OP user. For example, when the OP user's Policy is "If you aren't properly licensed, you can't own or possess a gun", the challenger makes a concession by stating "This sounds great" before the claim. In an attack relation, most of the interactions are Value to Value/Major Claim. This indicates that individuals usually make a rebuttal by describing what they think, and the process of persuasion is performed by expressing one's own opinion directly against another opinion. For example, when the OP user's Value is "you can(/should be able to) cycle or get public transport to shops and places of work" (and the Major Claim is "No one should personally own a car or other motor vehicles CMV"), the challenger makes a rebuttal by stating, "Public transport takes ages to get to the same place you're going to, and it often doesn't take you there directly, but through many intermediate steps".

## 4.3. Num of EUs in an argument

To investigate the strength of an argument (Wachsmuth et al., 2017) that has a stance attribute to the OP's view, we examined the number of EUs providing the rationale for the claim in an argument. For example, in Figure 2, an argument structure including Claim1 (in a positive post that attacks the Major Claim in the OP) comprises six EUs; thus, the number of EUs = 6. Figure 5 presents a histogram of the number of EUs in an argument that has a stance attribute. The results indicate that each post has no significant difference. This reveals that the quality of reasoning affects persuasion more than the number of reasons provided.

## 5. Conclusion

In this study, we proposed a novel annotation scheme for capturing the micro-level semantics and macro-level interactions of arguments. We annotated a corpus using our annotation scheme; the corpus consists of 4612 EUs, 2713 inner-post relations, and 605 inter-post relations in 115 threads of the ChangeMyView dataset. This corpus is a valuable resource for analyzing persuasiveness and training an argument mining system.

In the future, we plan to study the automatic identification and classification of EUs and their inner-post and inter-post relations. We also plan to investigate differences in persuasion strategies resulting from differences in topics.

## 6. Acknowledgments

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