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LPAttack: A Feasible Annotation Scheme for Capturing Logic Pattern of Attacks in Arguments

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Abstract

In argumentative discourse, persuasion is often achieved by refuting or attacking others' arguments. Attacking an argument is not always straightforward and often consists of complex rhetorical moves in which arguers may agree with a logic of an argument while attacking another logic. Furthermore, an arguer may neither deny nor agree with any logics of an argument, instead ignore them and attack the main stance of the argument by providing new logics and presupposing that the new logics have more value or importance than the logics presented in the attacked argument. However, there are no studies in computational argumentation that capture such complex rhetorical moves in attacks or the presuppositions or value judgments in them. To address this gap, we introduce LPAttack, a novel annotation scheme that captures the common modes and complex rhetorical moves in attacks along with the implicit presuppositions and value judgments. Our annotation study shows moderate inter-annotator agreement, indicating that human annotation for the proposed scheme is feasible. We publicly release our annotated corpus and the annotation guidelines.

Keywords: argument, counterargument, attack, logic, argumentation, reasoning, annotation, pattern, debate

1. Introduction

Argumentation plays a central role in human communication, where refuting or attacking others' arguments is a common persuasion strategy (Walton et al., 2010). *Attacks* in arguments can have different modes (Walton, 2009; Cramer and Guillaume, 2018) and often consist of complex rhetorical moves, e.g., one might attack the *conclusion* (i.e., the statement expressing position or belief of the arguer) while agreeing with a *premise* (i.e., statement providing support or reason for the conclusion) of the argument (Afantenos and Asher, 2014). Consider an example debate in Fig. 1, where opposing teams give two argumentative speeches. In the debate, the counterargument (CA) does not deny the *premise* of the initial argument (IA), i.e., *death penalty deprives the chance of rehabilitation of the criminals*. Instead, she implicitly agrees with it while denying the *conclusion* of the IA, i.e., *death penalty should be abolished* by giving more importance or value to the *death penalty* than the *rehabilitation of the criminals*. Although this value judgment is implicit in the CA speech, CA explicitly provides a reason behind her value judgment (bold text in CA). Automatically identifying such internal logic patterns can help a wide range of natural language processing (NLP) applications. For example, in an educational domain, this can help machines diagnose learners' arguments and provide feedback to the learners.

Prior studies in NLP that focused on *attacks* in arguments mainly worked on the classification of argumentative relations (e.g., support, attack, neutral), identifying attackable points in arguments, or counterargument generation (Stab and Gurevych, 2014; Deguchi and Yamaguchi, 2019; Kobbe et al., 2019; Jo et al., 2021a; Walton et al., 2008; Jo et al., 2020; Wachsmuth et al., 2018; Hua et al., 2019; Reisert et al., 2019; Alshomary et al., 2021; Jo et al., 2021b). Comparatively, less attention has been paid to identifying the logic pattern of attacks in arguments.

Although some recent studies (Reisert et al., 2018; Jo et al., 2021a) developed annotation schemes and logical mechanisms to capture the reasoning process behind support and attack relations where they exploited implicit causal links and sentiments, these studies did not capture other implicit information, e.g., presupposition or value judgments in arguments that also contribute to the underlying logical structure of attacks. Furthermore, none of these studies capture the modes of *attack* (e.g, whether the counterargument denies the conclusion or the premise of the attacked argument) and the complex rhetorical moves (e.g., agreeing with a premise while attacking the conclusion).

To address these gaps, we introduce LPAttack (**L**ogic **P**attern of **Attack**), a new annotation scheme that captures common modes of attacks and complex rhetorical moves in them as well as the implicit information and value judgments that contribute to the logical structure of attacks. Fig. 1 shows an example annotation. The logic pattern of IA speech is represented by our logic pattern, which can be interpreted as follows: *death penalty (=X) is considered a negative thing because death penalty suppresses chance of rehabilitation of the criminals (=Y), something good.* The logic pattern of CA speech then represents their value judgment on the *death penalty* and *chance of rehabilitation*

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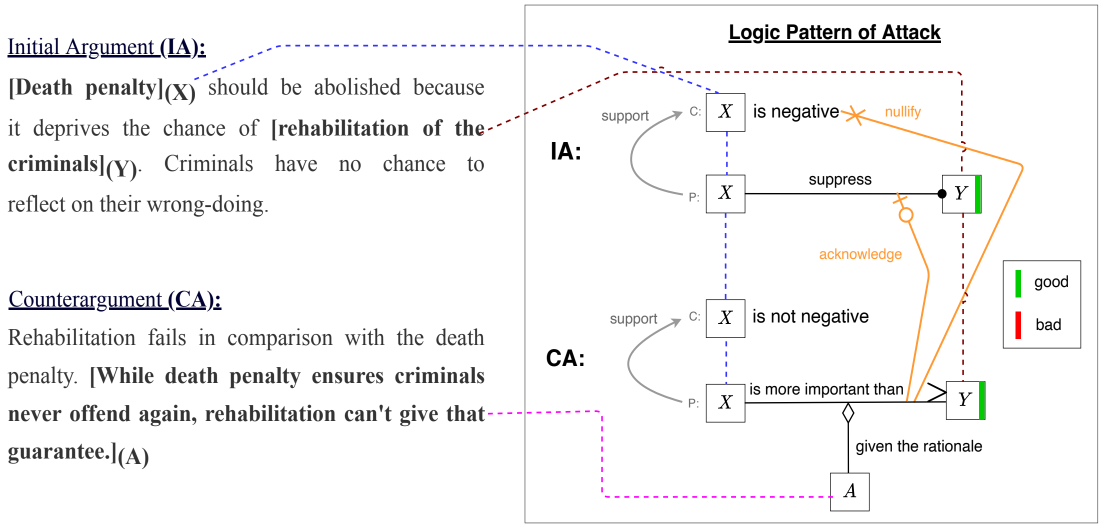

Figure 1: An example of logic pattern of attack of a debate captured by the proposed LPAttack annotation scheme.

of the criminals, where more value is given to the *death penalty*. This value judgment then attacks the conclusion of IA. Given that information, one can understand how and which part of the IA is attacked by the CA. Our contributions can be summarized as follows:

- We introduce LPAttack, a novel annotation scheme that captures the common modes and complex rhetorical moves in attacks along with the implicit information, presuppositions, or value judgments (§3).
- We conduct an annotation study using the proposed scheme that yields moderate agreement between two annotators indicating the feasibility of the human annotation for the scheme (§4).
- We provide the annotated corpus comprising logic patterns of attacks of 250 debates and the annotation guidelines as a publicly available resource to encourage future research[1].

2. Related Work

Computational analysis of argumentation has gained considerable attention in recent years because of its importance in many NLP applications such as essay scoring, argumentative writing support systems, and educational feedback. Common lines of work in this area include argumentative units (e.g., claim, premise) identification (Levy et al., 2014; Rinott et al., 2015; Stab and Gurevych, 2014), argumentative relations (e.g., support, attack, neutral) classification (Peldszus and Stede, 2015; Cocarascu and Toni, 2017; Niculae et al., 2017; Stab and Gurevych, 2014; Deguchi and Yamaguchi, 2019; Kobbe et al., 2019; Jo et al., 2021a), qualitative assessment of arguments (Persing et al., 2010; Persing and Ng, 2013; Persing and Ng, 2014; Persing and Ng, 2015; Persing and Ng, 2016; Rahimi et al., 2015; Wachsmuth et al., 2016; Habernal and Gurevych, 2016; Wachsmuth et al., 2017; Mim et al., 2019a; Mim et al., 2019b; Mim et al., 2021) and retrieval or generation of counterargument (Hua and Wang, 2018; Wachsmuth et al., 2018; Hua et al., 2019; Reisert et al., 2019; Alshomary et al., 2021; Jo et al., 2021b)

Lately, researchers have started focusing on one of the complex and challenging facet of argument analysis, i.e., capturing or explicating the encapsulated knowledge in arguments (e.g., causal knowledge, commonsense knowledge, factual knowledge) which are often implicit (Habernal et al., 2017; Hulpus et al., 2019; Becker et al., 2019; Becker et al., 2020; Al-Khatib et al., 2020; Becker et al., 2021b; Becker et al., 2021a; Singh et al., 2021; Saha et al., 2021). Although for a deeper understanding of argumentation, we also need to comprehend the underlying reasoning patterns of arguments, less attention has been paid to representing such underlying reasoning patterns and explicating the implicit information that contribute to these patterns.

We focus on this gap and address the problem of explicating internal logic pattern of attacks in arguments that comprise complex rhetorical moves and implicit causal information, sentiments, presuppositions as well as value judgments. Our inspiration for designing such an annotation scheme comes from Walton's argumentation schemes (Walton et al., 2008) which represent the common reasoning structures in arguments. For example, Walton's scheme of *Argument from Negative Consequences* has the conclusion that *A should not be brought about*, which is supported by the premise that *if A is brought about, then bad consequences will occur*. Although Walton's schemes explicate the unstated

[1] Our annotated corpus and annotation guidelines are publicly available at `https://github.com/cl-tohoku/LPAttack`

assumptions or propositions as a form of reasoning pattern, they are not intended to capture the logic pattern of *attacks*, i.e., how a counterargument attacks an argument. Note that each of Walton's schemes has a set of critical questions (CQs) that are used to judge if an argument fitting a scheme is good or fallacious. Some CQs for the above scheme are *How strong is the likelihood that the cited consequences will occur?*, *Are there other opposite consequences that should be taken into account?*. However, the CQs in Walton's schemes only specify the attackable points in an argument, they do not represent the reasoning pattern of attacks.

Some recent studies adopted Walton's schemes to represent the logic behind support and attack relations. One of these studies (Reisert et al., 2018) developed an annotation scheme that uses argument templates to capture reasoning patterns behind support and attack relations. Another study (Jo et al., 2021a) composed a set of rules specifying logical mechanisms that signal the support or attack relation. Although these studies identified implicit causal reasoning, sentiments, or factual contradiction in attacks, they did not capture other implicit information, such as contradictory causal reasoning, or assumptions or value judgments that significantly contribute to the logical structure of attacks.

One recent study (Saha et al., 2021) created commonsense explanation graphs that illustrate the commonsense reasoning process involved in inferring support and attack relations. However, the focus of this study is a commonsense explanation, not the reasoning pattern of *attack* (or support). Therefore, although this study exploited implicit causal knowledge, the fine-grained implicit knowledge explicated in this study is not effective in representing the logic pattern of *attacks*, which requires distinct coarse-grained implicit information, e.g., contradictions or value judgments in arguments.

Additionally, there is still no work in computational argumentation that captures the modes of attacks in arguments (e.g, whether the counterargument denies the conclusion or the premise of the attacked argument) or the complex rhetorical moves in them (e.g., agreeing with a premise while attacking the conclusion, providing a contradictory premise that leads to denying the conclusion etc.). Our work addresses these gaps by introducing an annotation scheme that can capture common modes of attacks, complex rhetorical moves in them as well as implicit causal reasoning, sentiments, presuppositions or value judgments that contribute to the logic pattern of attacks.

3. LPAttack Annotation Scheme

We hypothesized that the logic pattern of attacks in arguments is not uniformly distributed but is rather highly skewed, and following this hypothesis, we developed our annotation scheme to capture the common logic pattern of attacks in arguments.

3.1. Pre-Study and Scheme Design

To examine what sort of strategic moves, assumptions or value judgments are common during an attack, we conducted a preliminary qualitative analysis of how one argument attacks another (see Appendix for further details). For this pre-study, we selected 35 debates from the TYPIC dataset[2] (Naito et al., 2022) comprising multiple, diverse debate themes. Each debate comprises an argument and a counterargument conveyed by two opposing teams.

This analysis of the internal structure of attacks provided insights into how we can represent the attacking logic so that human annotation is plausible. Based on these insights, we designed our annotation scheme, defined the annotation guidelines, and formulated the task of capturing the logic pattern of attacks in arguments. In the following subsections, we describe our annotation scheme and the prliminary study findings.

3.1.1. Base Logic Patterns

Generally, when people argue *for* a belief, they show positive sentiment toward a concept of that belief. Conversely, when they argue *against* a belief, they exhibit negative sentiment toward a concept. For example, for the beliefs *"homework should be abolished"* and *"death penalty should be abolished"*, the arguers have an *against* stance. In both cases, they have *negative* sentiments toward the concepts of *homework* and *death penalty*. Now, counterarguments generally have the opposite stance and sentiment of the initial argument. For example, the counterargument *homework should not be abolished* has a *for* stance and a *non-negative or positive* sentiment toward the concept of *homework*. No matter how diverse the argument topic, the sentiment toward a certain concept is generally dependent on these *for* or *against* stances.

Argumentation Schemes (Walton et al., 2008) highlighted this fact and extensively utilized the positive or negative sentiment of the arguer toward a certain concept or consequence. Motivated by that, we designed two base patterns (shown in Fig. 2) for our scheme where the sentiments toward the main concept in the argument function as the *conclusion* of the argument. *Base pattern 1* represents the *against* stance of the initial argument and therefore presents the logic: {*Initial Argument*: X is negative; *Counterargument*: X is not negative} where X is a slot for the concept. Conversely, *Base pattern 2* represents the case where the initial argument has a *for* stance. The base patterns have two slots for premises: one in the initial argument and the other in the counterargument.

3.1.2. Relations and Attributes

To capture the logic of the *premise* that will support the conclusion (i.e., the sentiment toward the central

[2]This dataset is publicly available at https://github.com/cl-tohoku/TYPIC

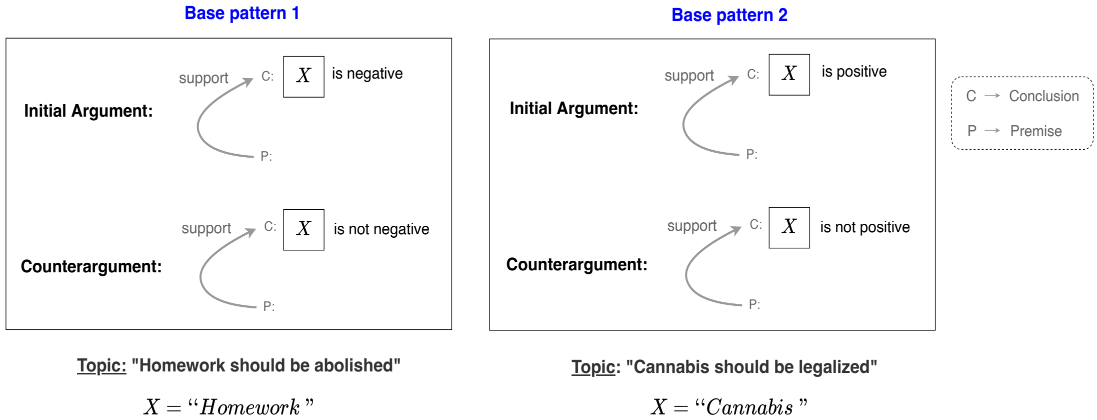

Figure 2: Base logic patterns with examples.

concept), we designed a set of relations and attributes. See Table 1 in the Appedix for an overview.

Causal relation Previous studies on the representation of implicit reasoning behind support or attack mostly adopted Argumentation Schemes (Walton et al., 2008) and have shown that a majority of arguments can be represented by the implicit causal links (Reisert et al., 2018; Al-Khatib et al., 2020; Jo et al., 2021a; Singh et al., 2021). In our pre-study, we observed similar phenomena. Most of the logics in arguments attacked or acknowledged by counterarguments can be represented by causality. For example, in Fig. 1, the logic of IA that the *death penalty deprives the chance of rehabilitation of the criminals* can be represented with the "suppress" causality: {*death penalty, suppress, the chance of rehabilitation of the criminals*}. We thus designed our annotation scheme around two causal relations, *"promote"* and *"suppress"* (henceforth, *"base relations"*).

Value judgement We observed that one common reasoning during an attack is based on value-judgements i.e., comparing two factors by giving more value or importance to one than the other. We have found two phenomena: (i) counterarguments give more importance to a certain concept of logic while implicitly acknowledging the logic, as shown in Fig. 1, and (ii) counterarguments neither acknowledge nor deny any logic of the initial argument, instead ignore it and deny the conclusion of the initial argument by providing new reasons presupposing that the new reasons have more value. Consider the following example:

(1) **Initial Argument (IA)**
...homework should be abolished (Conclusion)
...if homework were to be abolished, we could have more free time. As a result, we could do what we really wanted like club activities... (Premise)
Counterargument (CA)
...if homework is abolished, a number of people who don't study at all will increase.....To decrease a number of people who repeat years, homework is necessary...

In Example (1), the CA neither affirms nor denies the IA's logic, but ignores it and provides new reasons that deny the conclusion "homework should be abolished". The CA presupposes that the value or importance of {*if homework is abolished, a number of people who don't study at all will increase*} is greater than the value of {*if homework were to be abolished, we could have more free time*}, and this presupposition is implicit in the CA's argument. To represent the two phenomena of value judgments, we created the relation *"is more important or severe or has greater weight"*.

Contradiction Another common attacking strategy in counterarguments is providing contradictory logic that ultimately leads to denying the conclusion of the initial argument. One example is given below:

(2) **Initial Argument (IA)**
..death penalty should be abolished (Conclusion)
...death penalty is causing brutalization of modern society......it validates the notion that the taking of someone's life is a valid choice..... (Premise)
Counterargument (CA)
...death penalty sends a message that taking an innocent life will not be tolerated by a civilized society. Thus, it serves as an antidote to brutality...

Although the IA says: {*death penalty is causing brutalization of modern society*}, the CA says the opposite: {*it serves as an antidote to brutality*}. CA's logic contradicts IA's, which leads to denying the conclusion of the IA. To capture such contradictory logic, we invented the *"contradiction"* relation.

Logic denial/agreement To explicitly represent the denial of a premise's logic or conclusion, we created two relations, *"nullify"* and *"limit"*. These relations are considered the *"attacking relations"* in our scheme. We represent agreeing with a logic by the relation "acknowledgment".

Negation Counterarguments commonly *negate* (explicitly or implicitly) certain logic, especially causal reasoning, by providing some rationales or conditions. Consider the following example:

(3) **Initial Argument (IA)**
...homework should be abolished (Conclusion)
...if students are always given homework, they will always be waiting for instructions.....homework should be abolished so that students can study on their own initiative.... (Premise)
Counterargument (CA)
...students will hardly be able to study on their own without homework because continuous instructions or guidelines are needed for children to study or learn something new...

In Example (3), CA negates IA's logic {*homework should be abolished so that students can study on their own initiative*} by saying {*students will hardly be able to study on their own without homework*} and provides a reason behind it i.e., *"continuous instructions or guidelines are needed for children to study or learn something new"*. We developed the "negation" attribute and "rationale/condition" relation to represent such negation attribution and reasoning behind a logic.

Mitigation Instead of completely negating a logic, counterarguments often express that the severity of it can be mitigated. Consider the following example:

(4) **Initial Argument (IA)**
...death penalty should be abolished (Conclusion)
...death penalty causes executioner's suffering.....they feel that they are responsible themselves for killing the suspect.... (Premise)
Counterargument (CA)
..executioner's stress can be reduced by making sure that would-be executioners are fully prepared for the job and have a good mental support system

In this example, the CA does not completely negate IA's logic {*death penalty causes executioner's suffering*} instead partially negate it by saying {*executioner's stress can be reduced*}. We created a "mitigation" attribute to represent such partial negation attribution.

3.1.3. Slot-filling

To computationalize the task of capturing the logic pattern of attacks, we explored if it is possible to represent the logic patterns using only the information present in the argumentative texts. Our preliminary analysis suggested that it is fairly possible to represent the logic behind an attack without any external commonsense concepts. We thus decided to formulate the task of slot filling as a text-span selection task: annotators choose slot fillers in the base patterns from the given arguments.

3.2. Task Setting

The task of representing the logic pattern of attack for a given argument and counterargument consists of the following steps:

1. *Selection of base logic pattern and slot-filling:* A base logic pattern is selected based on the central stance of initial argument. Then, the slots of the pattern are filled with the central concept.

2. *Selection of relations and attributes along with text-spans:* Relations and attributes are chosen along with the text-spans from the given arguments to complete the base pattern by representing the logic of the premises.

Since there is no fixed template for representing the logic of the premises in the initial argument and counterargument of the base pattern, one important question is how many relations, attributes and text spans should be chosen for premise representations and how to choose them. In this regard, we took a summarization approach, in which we created a one or two line summary of the counterargument (CA) considering its main points and finding the logic in the initial argument (IA) that the CA attacks. If the CA attacks the IA's conclusion instead of attacking any logic behind the conclusion, then we created a one line summary of the IA's main points. After that, we chose suitable text spans, relations and attributes to represent that one or two line summary of the CA, the attacked logic or summary of the IA and how the CA attacks the IA (i.e., which part of the IA logic is denied and if the CA agrees with any of the IA logic). We refer to these representations as *CA-pattern*, *IA-pattern* and *attack-pattern*.

We set constraints on how many relations and attributes can be selected for each of these three representations. For IA-pattern, a maximun of two and for CA-pattern, a maximum of three relations or attributes can be selected. Using a base causal relation is mandatory for the IA-pattern and using *good* or *bad* attributes is prioritized in both cases. Choosing at least one attacking relation (i.e., nullify or limit) is mandatory to represent the attack-pattern. Note that the attack-pattern represents the relation between the CA-pattern and IA-pattern or CA-pattern and the conclusion of the IA.

We also set a constraint on how long the text spans should be. We specified that although text spans can be long up to two small sentences or one compound sentence, we should attempt to choose smaller text spans (e.g., short phrases) as much as possible. We also specified that we should choose such text spans that when we read the patterns as a standalone logic (i.e., without reading the debates), they are understandable.

4. Annotation Study

The key requirements for identifying the logic pattern of attacks in arguments are two-fold: (i) identify as many logic pattern of attacks as possible and (ii) make human annotation feasible. To verify whether our LPAttack scheme satisfies these requirements, we observed two metrics: (i) coverage of the scheme and (ii) inter-annotator agreement (IAA).

4.1. Setup

Two expert annotators participated in the annotation study and annotated the logic pattern of attacks independently using our annotation scheme[3].

We trained the annotators in a pilot annotation phase in which they were asked to annotate 20 debates. After the pilot annotation, we discussed the disagreements and, if needed, adjourned the annotation guidelines. One issue that we observed in the pilot annotations is that when we read the annotated patterns as a standalone logic (without reading the debates), some of them did not make complete sense because the chosen text spans had information gaps. To reinforce that the logic patterns are understandable on their own, we asked the annotators to write the text form of the logic patterns during our main annotation. For example, the text form of the logic pattern in Fig. 1 is as follows:

> IA: {*"death penalty" is negative*} because {*"death penalty" suppress ("chance of rehabilitation of the criminals" which is good)*}
>
> CA: {*"death penalty" is not negative*} because {*"death penalty" is more important/severe/has greater weight than "chance of rehabilitation of the criminals which is good" given the rationale/condition that "while executing prisoners is completely effective in ensuring...."*}

We expected that writing the text form would serve as a second check for the logic patterns and when the annotators read it separately from the debates, they will understand if there is an information gap or if the logic pattern is self-sufficient.

In our main annotation study, 50 debates were annotated by two annotators and 145 debates were annotated by a single annotator. For coverage and IAA, we report the results of dual annotations for 50 debates.

4.2. Coverage

We asked the annotators to mark an attacking strategy as "Not Applicable (NA)" if our scheme cannot represent it. We obtained 90% (45/50) coverage for the LPAttack scheme. This result validates our hypothesis that the logic pattern of attacks in arguments is not uniformly distributed but rather is highly skewed i.e., logic pattern of a wide range of attacks can be captured with a limited set of relations and attributes.

4.3. Inter-annotator agreement (IAA)

We measured the IAA for relations and attributes[4] using Cohen's (κ) (Cohen, 1960). For the calculation of the IAA, we consider IA-pattern, CA-pattern and attack-pattern (described in §3.2) as markables. Since we want to know how much the annotators agree on each of these logics and the overall debate, we applied two strategies for calculating IAA: (i) calculate IAA considering each markable and (ii) concatenate the three markables to have a single representation of the whole debate and calculate IAA.

We obtained Cohen's κ of 0.63 in case (i), which indicates a substantial agreement and in case (ii), we obtained a κ of 0.49, indicating moderate agreement (Artstein and Poesio, 2008; Spooren and Degand, 2010).

We also examined whether the text spans were the same[5] in cases where relations and attributes were agreed. Among the three markables, only IA-pattern and CA-pattern have text spans, and therefore we considered these two markables for the matching calculation but followed the same strategy as above (i.e., (i) and (ii)). In each of the markables, if all of the text spans matched exactly, we called it *exact-match*, if all of the text spans shared at least one word, we called it *lenient-match* (including the case where some of them have lenient matching while others have exact matching). We saw that in (i), 68% (47/69) of text spans were similar (43% (30/69) exact-match, 25% (17/69) lenient-match). For (ii), we obtained a 46% (12/26) match (19% (5/26) exact-match, 26% (7/26) lenient-match). See Table 3 in the Appendix for more detailed statistics.

4.4. Analysis of Annotations

We performed a manual analysis of the annotations in order to examine the correctness of the logic patterns, disagreements between the annotators and common attacking strategies captured by these annotations.

Correctness of the logic patterns We determined how many annotated logic patterns were correct i.e., the logic patterns capture the essence of the attacks and are understandable enough when read independently of the debates. We adopted the following strategy:

- Exact logic pattern match between annotators ⇛ mark as a correct logic pattern
- Non-exact match between annotators ⇛ manually check the logic patterns and discuss with the annotators ⇛ mark as correct or incorrect based on the results of the discussion

Following the above strategy, we found that 90% (45/50) of annotations of one annotator were correct whereas 86% (43/50) of annotations by the other annotator were correct. Both annotators had incorrect patterns for two of the debates. For four of the debates, one annotator chose "NA", whereas the other had correct patterns. For one of the debates, one annotator chose "NA", whereas the other had an incorrect pattern. This result indicates that having at least two annotations for a single debate provides a substantial likelihood of obtaining a correct annotation from one of the annotators.

[3]We use diagrams.net for annotation.

[4]We ignore calculating the agreement for the selection of base pattern since all the debates used in the annotation study has the same base pattern (i.e., base pattern 1).

[5]While we are aware of the work of Zeyrek et al. (2013), we did not apply any Kappa statistic on the text spans since the chance agreement is expected to be rare in our task.

Initial Argument (IA):

.....the **[death penalty]$_{(X)}$** should be abolished.... We are going to abolish the **[death penalty]$_{(X)}$** all over the world and introduce a **[life-imprisonment system]$_{(Y)}$**..... Our claim is that the death penalty deprives the chance of **[rehabilitation of the criminals]$_{(Y)}$**...... The criminal has no chance to reflect on what they have done. Life imprisonment system is a very severe punishment. Criminals are restricted of their freedom all day. They need to continue to apologize for the rest of their life while thinking about their victims....

Counterargument (CA):

They said that we should sentence prisoners to life instead of death so they can be rehabilitated. However, the reality is that **[a life spent in prison creates individuals who are unable to function when returned to society]$_{(A)}$**. These prisoners have become institutionalized, meaning they have become dependent on the rigid structure of the prison system. **[By being imprisoned for years, often in isolation and deprived of meaningful stimuli, these inmates gradually lose their life skills and ability to interact with others]$_{(A)}$**..... The death penalty, makes no claims to accomplish rehabilitation. Its goal is more straightforward: to deter future crime.

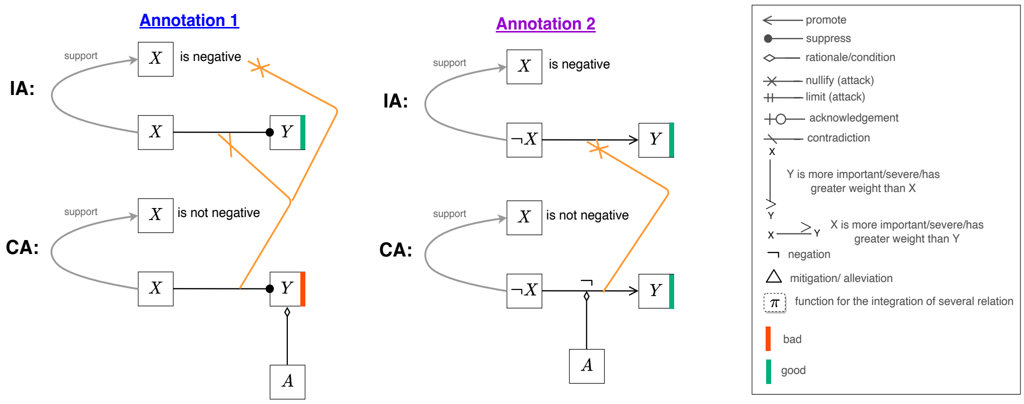

Figure 3: Example of debate where two annotators have different interpretation.

Disagreements between annotators There are generally two types of disagreements between the annotators: (i) the same interpretation of the debate but different logic patterns and (ii) different interpretations of the debate. One example of case (i) is given below:

> Annotation 1: {*"homework" is more important than "free time" given the condition/rationale that "homework can establish basic foundation of studying"*}

> Annotation 2: {{*"homework" promote "establish basic foundation of studying"*} *which is more important/severe/has greater weight than* {*"homework" suppress "free time"*}}.

In this example, both annotations have the same interpretation i.e., *homework is more important than free time because it establish basic foundation of studying* but the interpretation is represented differently.

One important factor that we noticed is that in all of the cases of (ii), where annotators had a different interpretation of the debates, one of the annotations was found incorrect. One example of such case is shown in Fig. 3. In this example, the interpretation of CA-pattern is different in two annotations i.e., {*death penalty suppress life imprisonment system which is a bad thing*} and {*no death penalty doesn't promote rehabilitation of the criminals*}. Although both of the annotated patterns are understandable without reading the debates, *Annotation 1* has been marked as incorrect because in this debate, CA does not exactly express that life imprisonment is bad, but rather expresses that the reason behind abolishing the death penalty is the rehabilitation of the criminals whereas even if we abolish the death penalty, it does not result in rehabilitation in life imprisonment, and *Annotation 1* has failed to capture that notion.

We also see that many disagreements happen in the choice of text spans. When we manually checked the debates, we noticed that even when some interpretations are quite the same such as in case (i), the text spans are different. This is because sometimes, two or more sentences express the same meaning and annotators choose text spans from these different sentences. Consider the following example:

> Annotation 1: {*"homework" promote "learns that the way to succeed is by making schedule"*} *is more important/severe/has greater weight than* {*"homework" suppress "do more of what we really wanted"*}

> Annotation 2: {*"homework" promote "learns the importance of scheduling"*} *is more important/severe/has greater weight than* {*"homework" suppress "free time"*}.

In both cases, the text spans *"learns that the way to succeed is by making schedule"* and *"learns the importance of scheduling"* basically have the same interpretation but were chosen from different sentences and therefore are considered mismatched.

Besides, when the CA attacks the IA's conclusion, annotators often choose different main points to represent the premise of the IA and, in such cases, text spans

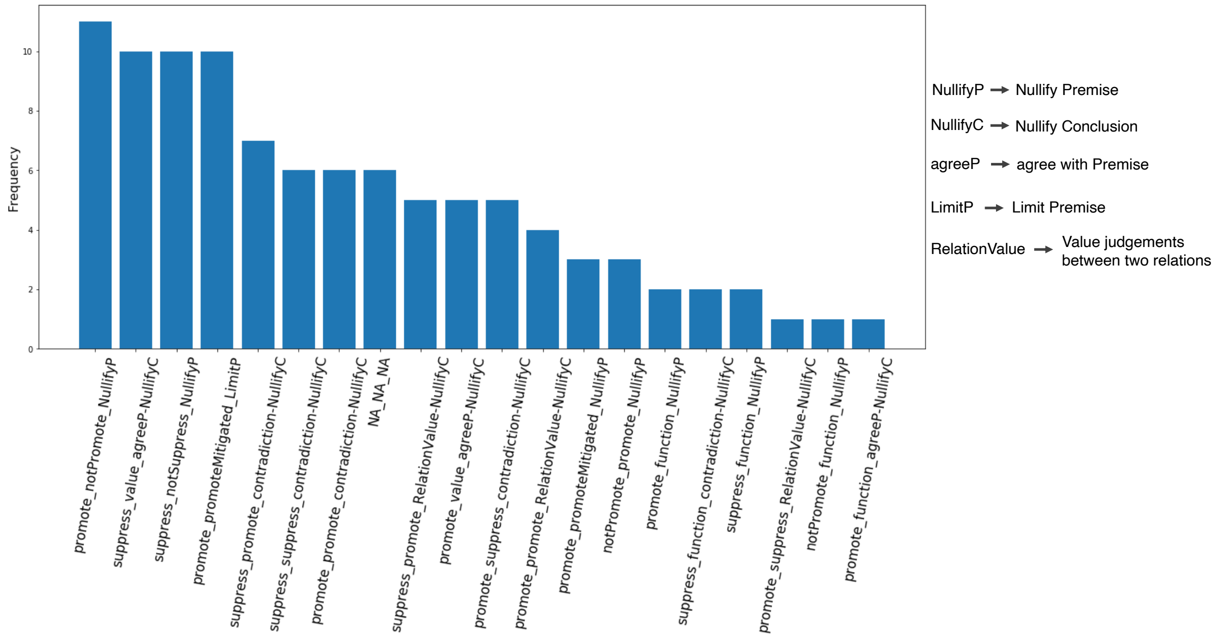

Figure 4: Distribution of logic patterns

do not match. In the above example we see that the representation of the main points of the IA is different i.e., *'do more of what we really wanted'* and *'free time'*, since the CA does not attack these premises.

Common attacking strategies captured by the annotations To examine what sort of common rhetorical moves, assumptions, or value judgments in attacks are captured by our annotations, we looked into the distribution of relations and attributes used to annotate the debates. Figure 4 shows this distribution. We see that, the most common logic patterns are "attacking a premise by negating it", "value judgements between two concepts of a premise that leads to agreeing with the premise but denying the conclusion", "providing a way for mitigating the consequence of a premise that leads to agreeing with the premise and nullifying it at the same time" and "providing a contradictory premise that leads to denying the conclusion". Moreover, we observe that "value judgement between two causal relations" also happens quite often.

5. Discussion and Future Work

In our annotation study, we observed that although the initial arguments were causal arguments, some logics in the arguments were evaluative judgments e.g., "death penalty is cruel" or "A truly just society can do without the death penalty" and the counterarguments focused on those logics. In such cases, the annotators failed to annotate the attacking strategy. In the future, we would like to enrich our scheme so that these sorts of logics in attack can be captured.

We also plan to have a second annotation for the 145 debates in our corpus that currently have only a single annotation. Besides, we plan to perform a voting between the two annotations to choose a single representation for each attacking strategy based on majority voting. In addition, we intend to apply the LPAttack annotation scheme on top of other existing debate corpora. Furthermore, we plan to formulate the task of automatic identification of logic pattern of attacks from given arguments and counterarguments.

We acknowledge the fact that capturing the logic pattern of attacks is a challenging task, especially when the arguments are long, and there is many room for improvements.

6. Conclusions

We proposed LPAttack, a feasible annotation scheme for capturing the underlying logic pattern of attacks in arguments. LPAttack is designed to capture the common strategic moves, assumptions and value judgments during attacks in arguments. Our annotation study showed that even with a limited set of relations and attributes, we could capture the logic pattern of a wide range of attacks (90%) in a debate corpus of multiple, diverse debate themes. The results also showed a moderate inter-annotator agreement (Cohen's $\kappa = 0.49$) between two annotators, verifying the feasibility of the proposed scheme.

7. Acknowledgements

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Appendix

Pre-Study and LPAttack scheme design The initial design of the annotation schemes, guidelines, and tasks were developed by the authors of this paper. Two untrained annotators explored the initial designs and helped improve the overall design and guidelines. The primary feedback from the annotators included suggestions for a detailed description for each of the relations and attributes, creating categories for them, and having a prioritization map for these relations and attributes.

During our pre-study, we noticed that sometimes the counterargument shows strong opposite sentiment toward an argument e.g., {*Argument: X is negative; Counterargument: X is positive*} and sometimes the opposite sentiment of the counterargument is not that

Relations	Description	Example
promote	represents something causing/ encouraging another thing	no homework *promote* free time
suppress	represents something hindering/ preventing another thing.	homework suppress free time
rationale/condition	represents writer's reasoning or justification behind a relation or attribution.	homework is more important than free time given the *rationale/condition* that homework is part of education
X → Y: (Y) is more important/severe/ has greater weight than (X) X → Y: (X) is more important/severe/ has greater weight than (Y)	(i) represents some relation has higher value than another or (ii) some concept or element has higher value than another	(i){no homework promote people fail in exam} which *is more important/ severe/ has greater weight* than {no homework promote free time}, (ii) Example in Fig. 1
contradiction	represents opposing logics	{homework promote "problems in family"} *contradicts* {homework promote good family relation}
acknowledgement	represents agreement between relations	Example in Fig. 1
nullify (attacking relation)	represents denying a relation or logic	Example in Fig. 1
limit (attacking relation)	represents agreeing with and denying a relation at the same time	{death penalty promote executioner's suffering can be mitigated given the condition that executioners have a good mental support system} which *limit* {death penalty" promote executioner's suffering}
π function	represents joining of two or more relations	joining the two relations {homework suppress free time} and {free time promote unproductive activities} would produce the relation {homework suppress unproductive activities}

Attributes	Description	Example
¬ negation	represents negation form of a relation or concept	{homework *doesn't* promote free time} or {*no* homework promote free time}
△ mitigation	represents mitigated form of a relation	{death penalty promote executioner's suffering can be *mitigated* given the condition that executioners have a good mental support system}
good	represents positive feeling of the arguer towards a concept	{homework" should be abolished because homework suppress free time}. Here "free time" is a *good* thing according to the arguer
bad	represents positive feeling of the arguer towards a concept	{death penalty should be abolished because death penalty promote executioner's suffering }. Here, "executioner's suffering" is a *bad* thing according to the arguer

Table 1: Relations and attributes in LPAttack scheme

	Homework should be abolished
PM-1	Abolishing homework will give students more free time
PM-2	Forcing students to do homework will make them passive in character
PM-3	It is not good for students to be obliged to study by their teachers or parents
PM-4	Students have memorized the incorrect way to study with homework
PM-5	Schools should take the responsibility for children's academic skills, not parents at home

	Death penalty should be abolished
PM-1	Death penalty is inhumane punishment
PM-2	Abolishing death penalty will prevent the situation of ending the life of innocent people
PM-3	Because of the high stress on the executioner, death penalty should be abolished
PM-4	The death penalty deprives criminals of the opportunity for rehabilitation
PM-5	Society is being brutalized by the death penalty

Table 2: Main points of the initial arguments of the debates in the TYPIC corpus for which counterarguments are written

strong e.g., {*Argument: X is negative; Counterargument: X is not negative*}. However, the strength of the opposite sentiment usually depends on human perception and may thus vary. To reduce the complexity and confusion during human annotation, we only maintained the representation of the less strong opposite sentiment of counterargument as shown in Fig. 2.

Source data For our preliminary and annotation studies, we utilized the debates from the TYPIC dataset (Naito et al., 2022). This dataset has 1,000 parliamentary style debates where given a topic, two opposing teams, Prime Minister (PM) and the Leader of the Opposition (LO) argue by taking a position in favor and against the topic respectively. In each debate, the PM speech acts as the *initial argument* and the LO speech acts as the *counterargument*. The corpus comprises 10 PM speeches on two topics: *"Homework should be abolished"* and *"Death penalty should be abolished"*. Table 2 shows the main points of these PM speeches. For each PM speech, there are 100 LO speeches. The arguments of 8 PM speeches out of 10 are causal arguments (underlined in the table).

Since our scheme is designed around two causal relations "promote" and "suppress", when we chose debates, we only chose these 8 PM speeches (initial arguments) for annotations whose arguments are causal and then, we randomly chose the LO speeches (counterarguments) associated with these PM speeches.

	Common	Overlapping	Different
Interpretation	33	8	9
Logic pattern	27	15	8
Text span	21	18	11

Table 3: Detailed statistics of disagreement in interpretations, logic patterns and text spans. Each cell indicates the number of speeches whose annotations given by two annotators are common, overlapping, or different (see the text for the definition).

Rules for calculating IAA: One factor to consider during the IAA calculation is that in our scheme, we kept the flexibility of human representation i.e., the same interpretation can be represented in a slightly different way. For example, "no homework promote free time" has the same meaning as "homework suppress free time", but they are different representations. To handle such different representations that generally have the same meaning, we created some rules to consider these different representation as the same. Figure 5 shows these rules. As shown in the figure, we considered the representations "no X promote Y" and "X suppress Y" as the same (marked as *Causal Type A*) since they have the same meaning. One of our rules consider rationale/condition relation as an auxiliary in certain cases where having or not having it does not affect the understanding of the logic. For example, in the case of the logic, {{no homework promote people fail in exam *given the rationale/condition that not doing homework will lead to lack of preparation*} which is more important or severe or has greater weight than {no homework promote free time}}, even if we remove the rationale/condition relation, the interpretation is understandable. We ignored this relation in such cases during the calculation of IAA.

Disagreements in annotations Table 3 displays the number of speeches whose interpretations, logic patterns, and text spans selected by the two annotators are *common*[6] (i.e., two annotations are the same[7] in both the initial argument and counterargument), *overlapping* (i.e., two annotations are the same only in the initial

[6]For *interpretation*, we consider if the attacking point in the initial argument has same interpretation, i.e., if the *conclusion* of the initial argument is attacked in both annotations, we consider them *common* and ignore the premise interpretation of the initial argument.

[7]For text spans, we consider them *same* if they are *exact* or *lenient* match.

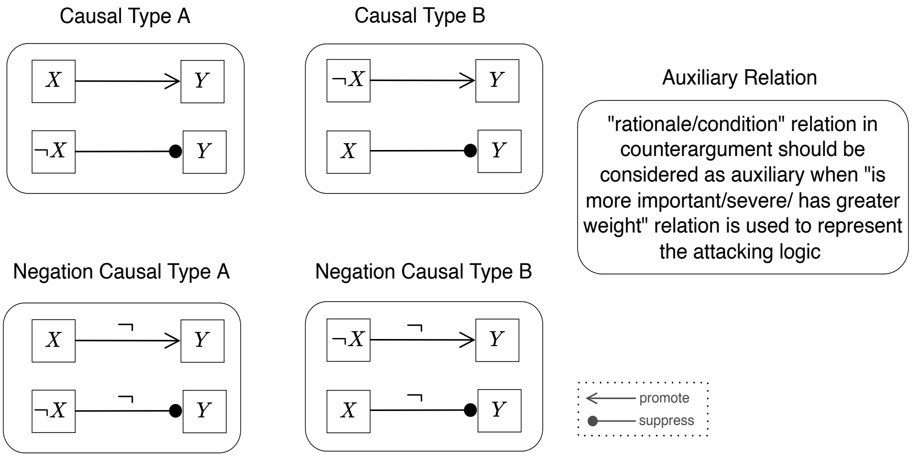

Figure 5: Rules for calculating inter-annotator agreement (IAA)

argument), or *different* (i.e., otherwise). See §4.4 for reasons behind these disagreements.

Annotation examples of the logic pattern of attacks To provide a better understanding of what the annotated logic patterns look like and what sort of text spans are chosen from the given arguments, we provide annotation examples in Fig. 6, 7, and 8.

Initial Argument (IA):
Hello, everyone. Today's topic is "Death penalty should be abolished". We define that the [**death penalty]**(X) should be abolished and instead of the death penalty, we propose that the suspected are sentence to life in. We have two points. The first point is [**"Executioner's suffering"]**(Y). The second point is "Cruelty of death penalty". I will explain the first point. In present situations, a person who executes the death penalty for a criminal whose death penalty has been confirmed by a trial suffers a lot. Some methods of the death penalty include hanging and using gas chambers. Let me illustrate the case of hanging in Japan. A prisoner does not know when they will be executed until the day of execution. At the day of execution, they first enter the teacher's room and write a farewell letter. Then, they go to the antechamber for execution and are separated from the execution room by a curtain. The convict on death row is blindfolded and handcuffed, and a curtain is closed to the execution room. Finally, they go to the execution room. A rope is hung around their neck and they stand on a tread plate marked in the center of the room. Then, multiple prison officers push the button to open and close the tread, and the convict on death row falls. Those executioners feel strong stress. They don't know which button is actually connected to the input of the tread. They feel that they are responsible for killing the suspect on death row by their own hands. Executers' stress is extremely overwhelming. That's why the death penalty should be abolished. Thank you.

Counterargument (CA):
They said that prison workers who take part in executions suffer stress, so the death penalty should be eliminated. However, instead of abolishing a punishment that the Constitution endorses, we should find ways to effectively deal with executioner stress. Obviously, if the job involves carrying out executions on a daily basis, without relief or counseling, the executioner is going to feel bad and probably exhibit PTSD. We can combat that by [**making sure would-be executioners are fully prepared for the job, that they are mentally sound and have a good support system]**(A). In addition, we can relieve the stress of dealing with executions day in and day out by rotating the task so the number of executions carried out by a single guard is limited. In this way, executioner stress is reduced and the ultimate penalty can remain a legal option for the worst crimes.

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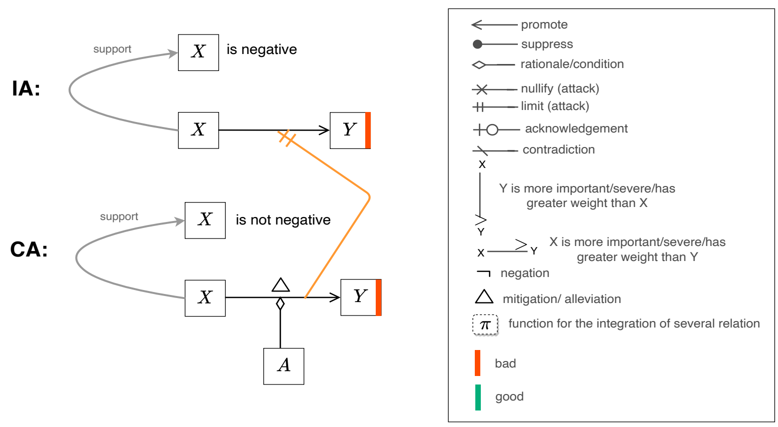

Figure 6: Annotation example of logic pattern of attack of a debate

Initial Argument (IA):
Hello everyone. Today's topic is "**[Homework]**$_{(X)}$ should be abolished". We have two points: The first point is "free time" and the second point is "decrease burden on teachers". I will explain the first point of **["free time"]**$_{(Y)}$. We believe that if homework were to be abolished, we could have more free time. As a result, we could do more of what we really wanted like club activities, hobbies, or playing with friends. In my case, I go to tennis club after class until 5:00 pm and then I go to cram school until 8:00 pm. After this full day, I arrive at my home around 8:40 pm to eat dinner and take a shower. At nearly 10:00 pm I start my homework. I have a lot of homework. As a result, I go to bed late at night at nearly 1:00 am in the morning and I don't have the opportunity to sleep for a long period of time. It is not healthy. Therefore, homework should be abolished. Thank you.

Counterargument (CA):
They said that if we don't have homework, we have more free time and more healthy day. And teachers' burden will be decreased. However, a number of people who don't study at all will increase. People are forgetful, so not doing homework leads to insufficient fixing of class contents of the day. Thus during a week immediately before a semester test people who don't do class reviews will be more busy and then, they will fail in the examination for lack of preparation. To decrease **[a number of people who repeat years]**$_{(A)}$, homework is necessary.

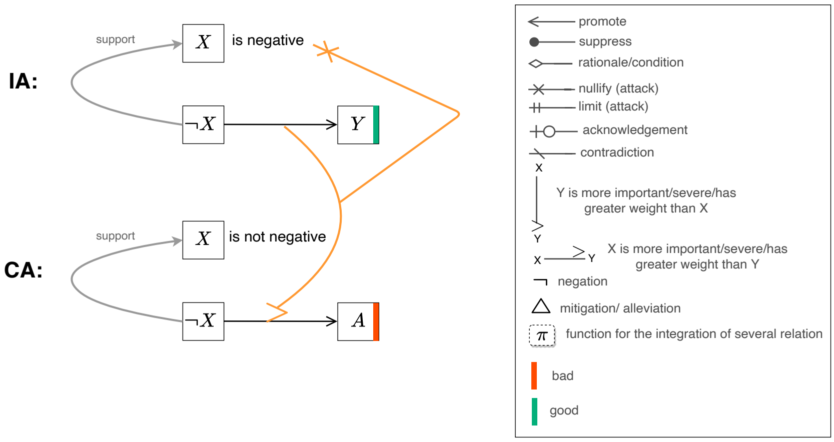

Figure 7: Annotation example of logic pattern of attack of a debate

Initial Argument (IA):
Hello everyone. Today's topic is "**[Homework]**$_{(X)}$ should be abolished". We have two points: The first point is "free time" and the second point is "decrease burden on teachers". I will explain the first point of **["free time"]**$_{(Y)}$. We believe that if homework were to be abolished, we could have more free time. As a result, we could do more of what we really wanted like club activities, hobbies, or playing with friends. In my case, I go to tennis club after class until 5:00 pm and then I go to cram school until 8:00 pm. After this full day, I arrive at my home around 8:40 pm to eat dinner and take a shower. At nearly 10:00 pm I start my homework. I have a lot of homework. As a result, I go to bed late at night at nearly 1:00 am in the morning and I don't have the opportunity to sleep for a long period of time. It is not healthy. Therefore, homework should be abolished. Thank you.

Counterargument (CA):
They said that if homework were to be abolished, we can enjoy more free time. However, it's not true. Because instead of doing homework, we have to **[take time to catch up with classes]**$_{(A)}$. Please recognize purpose of homework. Homework exists to facilitate our efficient review and preparation for classes such as practice of using some formulas, or writing kanji. That's why even without homework, we have to study by ourselves anyway to understand classes. But problem is; we will take time to decide contents and review knowledge. Because we don't know what we should do. Given that, we can't have more free time on Gov side and homework rather allow we to study efficiently and have more free time.

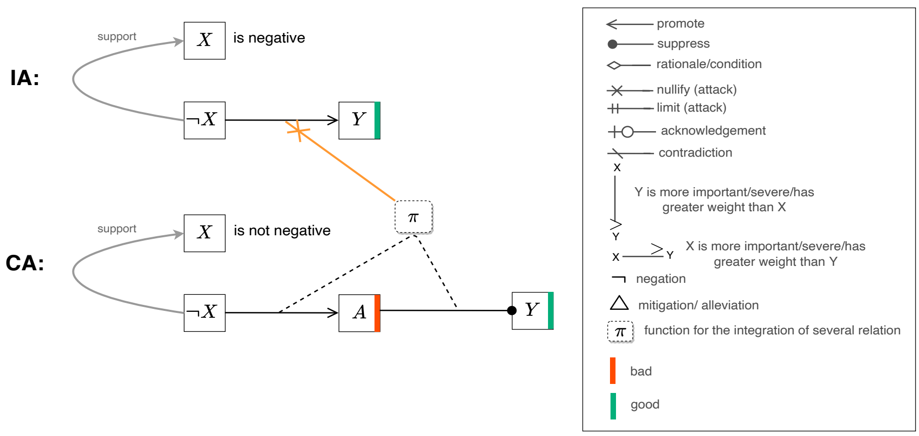

Figure 8: Annotation example of logic pattern of attack of a debate