Employing Argumentation Knowledge Graphs for Neural Argument Generation

Khalid Al-Khatib1 Lukas Trautner2 Henning Wachsmuth3 Yufang Hou4 Benno Stein5

1 Leipzig University, Germany, khalid.alkhatib@uni-leipzig.de
2 University of Erlangen-Nuremberg, Germany, lukas.trautner@fau.de
3 Paderborn University, Germany, henningw@upb.de
4 IBM Research Europe, Ireland, yhou@ie.ibm.com
5 Bauhaus-Universität Weimar, Germany, benno.stein@uni-weimar.de

Abstract
Generating high-quality arguments, while being challenging, may benefit a wide range of downstream applications, such as writing assistants and argument search engines. Motivated by the effectiveness of utilizing knowledge graphs for supporting general text generation tasks, this paper investigates the usage of argumentation-related knowledge graphs to control the generation of arguments. In particular, we construct and populate three knowledge graphs, employing several compositions of them to encode various knowledge into texts of debate portals and relevant paragraphs from Wikipedia. Then, the texts with the encoded knowledge are used to fine-tune a pre-trained text generation model, GPT-2. We evaluate the newly created arguments manually and automatically, based on several dimensions important in argumentative contexts, including argumentativeness and plausibility. The results demonstrate the positive impact of encoding the graphs’ knowledge into debate portal texts for generating arguments with superior quality than those generated without knowledge.

1 Introduction
Arguments are our means to build stances on controversial topics, to persuade others, or to negotiate. Automatic argument generation has the potential to effectively support such tasks: it may not only regenerate known arguments but also uncover new facets of a topic. Existing argument generation approaches work either in an end-to-end fashion (Hua and Wang, 2018) or they are controlled with respect to the argument’s topic, aspects, or stance (Gretz et al., 2020; Schiller et al., 2021). In contrast, no approach integrates external knowledge into the generation process so far, even though knowledge graphs have been shown to be useful for supporting text generation models in other areas (Koncel-Kedziorski et al., 2019a; Ribeiro et al., 2020).

Previous research has proposed argumentation knowledge graphs (AKGs) that model supporting and attacking interactions between concepts (Al-Khatib et al., 2020). Such an AKG may assist argument generation models in different ways. For example, meaningful prompts on controversial topics can be constructed from an AKG with simple hand-defined rules, such as ‘geoengineering reduces atmospheric greenhouse gas’ for generating an argument on ‘geoengineering.’ Alternatively, an AKG may be employed to control the generation, making arguments adhere to knowledge covered in the graph. We hypothesize this to be particularly beneficial for the quality of arguments in terms of factuality, the richness of evidence, and similar.

This paper concentrates on such controlled argument generation, investigating for the first time the ability to generate high-quality and content-rich arguments by integrating knowledge from AKGs into standard neural-based generation models. To this end, we exploit multiple manually and automatically created knowledge graphs, devoting particular attention to causal knowledge (Al-Khatib et al., 2020; Heindorf et al., 2020). Causality plays a major role in argumentation due to its frequent usage in real-life discussions; argument from cause to effect and argument from consequences are frequently used argumentation schemes (Feng and Hirst, 2011; Reisert et al., 2018).

To utilize AKGs for argument generation, we collect argumentative texts from diverse sources such as online debate portals. In these texts, we find arguments that contain instances of the knowledge covered in the graphs. We encode this knowledge as keyphrases in the arguments. Unlike Gretz et al. (2020) and Schiller et al. (2021), our keyphrases cover multiple aspects and stances related to the same topic. The resulting texts are used to fine-tune a transformer-based generation model, GPT-2 (Radford et al., 2019). The underlying hypothesis is
that GPT-2 will use the keyphrases to constrain the generation of arguments. During application, we provide the model with knowledge (as keyphrases) to obtain new arguments that further elaborate the knowledge. Figure 1 gives an overview of the main steps of our approach.

We evaluate the ability of our approach to generating new arguments for a variety of claim-like prompts: 400 generated arguments are manually assessed for their relevance to the prompt, argumentativeness, content richness, and plausibility. As a recent study indicates the adoption of bias from argumentative source data in word embeddings (Spliethöver and Wachsmuth, 2020), we also inspect potential social bias and abusive language in the generated arguments. Moreover, we evaluate the generated arguments automatically using recently developed argument mining techniques, in order to then examine correlations between manual and automatic evaluations. The results reveal an evident benefit of using the graphs’ knowledge in generating controlled arguments that are rich in content and plausible. However, we also observe the presence of social bias in the outputs of GPT-2, suggesting the need for careful postprocessing step in argument generation.

Both the resources and the code developed in this paper will be made available.¹

2 Knowledge Graphs for Argumentation

We use knowledge graphs (KGs) to plan the content of an argument to be generated and to control its talking points. A talking point is a specific aspect related to a given discussion topic. For instance, “health” is a talking point related to “smoking.”

In this section, we describe the construction of three graphs related to argumentation: (1) a ground-truth argumentation knowledge graph, which is utilized based on Al-Khatib et al. (2020), (2) a generated argumentation knowledge graph, which is newly constructed from a set of argumentative texts, and (3) a causality graph, which is built upon Heindorf et al. (2020).

2.1 Ground-truth Knowledge Graph

Al-Khatib et al. (2020) propose a graph model that encodes the knowledge contained in arguments as relations (identified as the graph’s edges) between concepts (identified as the graph’s nodes). A concept is a noun phrase that represents an entity, an event, or an abstract idea. A relation represents the positive or negative effect that a concept has on another one. A relation is positive if concept A promotes/causes/increases concept B, and it is negative if concept A suppresses/prevents/stops concept B. A concept has two types of attributes: (1) groundings, which link concepts to the corresponding entries in a knowledge base such as Wikidata, (2) consequences, stating whether a concept is viewed as predominantly good or bad.

We slightly modify the outlined model to render the processing of the graph more amenable for our purposes. Instead of considering consequences as concept attributes, they are here modeled as an effect relations type: a good consequence is mapped to a positive effect, and a bad consequence to a negative effect. For example, “smoking is bad for health” is mapped to “smoking has a negative effect on health.”

Accordingly, we populate the graph using the ar-

¹https://github.com/webis-de/ACL-21
Table 1: Counts of nodes and edges in the three graphs, the latter separated into positive and negative effect.

| Graph            | #Nodes  | #Edges  | #Pos. | #Neg. |
|------------------|---------|---------|-------|-------|
| (A) Ground-truth | 4,607   | 9,100   | 4,904 | 4,196 |
| (B) Generated    | 19,181  | 14,643  | 13,003| 1,640 |
| (C) Causality    | 74,356  | 179,701 | 179,701| 0     |

Graph Construction

We followed the scheme of the manually generated argumentation knowledge graph described in the previous section, and identified concepts and relations in argumentative texts using the argument knowledge relation extraction approach of Al-Khatib et al. (2020). The approach comprised two main steps: (1) identifying whether a given text encodes an effect relation, and its type if any, and (2) finding the concepts of the identified relation. Specifically, for a given sentence, we extracted zero, one, or several argument knowledge relation instances in the format \{concept A, positive/negative effect, concept B\}.

We segmented all the arguments from the two sources into sentences and applied the argument knowledge relation extraction approach to all sentences, obtaining 11,537 and 17,688 relation instances from args.me and Kialo, respectively.

Our new automatically-generated argumentation knowledge graph is built on top of these post-processed argument knowledge relation instances. Table 1 (row B) shows statistics of the new graph. It contains 19,181 nodes and 14,643 relations.

2.3 Causality Knowledge Graph

Recently, Heindorf et al. (2020) built a new causal knowledge graph which focuses on causal relations.
between concepts. The construction of the KG was done by applying different information extraction techniques including bootstrapping, linguistic patterns, and sequence tagging on ClueWeb12 and Wikipedia. The corpus comes with two versions: a high-recall version with more than 11 million causal relations and a high-precision version with only around 200k relations. We make use of the high-precision version to build a new graph which is inline with the scheme of the two argumentation knowledge graphs described above. In particular, we map the cause relation to the positive effect relation since the former is a special case of the latter. We further exclude some noisy instances that contain the same concepts in a causal relation (e.g., concept A causes concept A). In total, the final graph comprises 74,356 nodes and 179,701 edges as shown in Table 1 (row C).

2.4 Graph Analysis

Table 2 shows examples of the knowledge in the graphs. To gain insights into the three graphs and their relationships, we analyzed the central concepts in each graph and the overlap between them.

**Graph Central Concepts** We use the centrality degree to get the most central nodes in each graph. For the graph constructed manually, we found the most central nodes to be controversial topics as well as some general concepts that affect our lives in general. A similar observation can be made for the second knowledge graph, but with an additional set of controversial topics. Most central concepts in the causality graph are related to health. Table 3 shows examples of the central concepts in the graphs.

**Graph Overlap.** We checked overlap between nodes among the three graphs. The ground-truth graph and the generated graphs have 1,424 overlapping nodes. Concretely, 908 nodes from the ground-truth KG match with those from the causality KG, and 2,326 from the generated KG match with those from the Causality KG. We note that the causality graph, albeit mostly covering general and health-related concepts, overlaps with the other two graphs in several controversial topics such as “climate change” and “abortion”.

3 Neural Argument Generation

We now present our approach to integrate the argumentation knowledge graphs such as those described above into a neural text generation model.
Animal studies suggest ... 'marijuana»positive»physical-dependence', 'mariguana»positive»problems'] @

While this way of matching and encoding has limitations, it has shown good results in practice when used with pre-trained neural models (Witteveen and Andrews, 2019; Cachola et al., 2020).

3.3 Neural Language Model Fine-tuning
We use our text-knowledge encoding dataset to fine-tune the GPT-2 neural language model (Radford et al., 2019) for argument generation. Since GPT-2 cannot deal with graph structure as input directly, we fine-tune it on all paragraphs, including those with encoded relations as textual representations (i.e., keyphrases). We expect to thereby leverage the powerful generation capabilities of GPT-2 while biasing it to generate texts related to the encoded relations.

It is worth noting that, in training, we encode multiple relations at once and the generated arguments are paragraphs. The encoded relations are often related to different aspects of the same topic. This is different from previous studies (Gretz et al., 2020; Schiller et al., 2021) which only focus on generating an argumentative sentence based on a single topic or one aspect/stance of a topic. As a result, we expect that our fine-tuning strategy based on knowledge graphs can assist users to plan several “talking points” and generate the corresponding argument which covers the different aspects.

4 Experiments and Results
In this section, we report on the manual and automatic evaluation of our approach from Section 3 to employ the three argumentation knowledge graphs from Section 2 for neural argument generation:

A. The ground-truth graph
B. The generated graph
C. The causality graph

4.1 Experimental Set-up
We used the following experimental setup:

Model Parameters In all experiments, we fine-tuned the pre-trained GPT-2 model with 127M parameters using gpt-2-simple library.\(^3\) For argument generation, we follow Gretz et al. (2020) in setting top_k to 40 and temperature to 0.7. Also, we set the batch_size to 2 and the steps to 1500. We specify the length of the generated arguments to be 100 (approximately, the mean number of words of the arguments in our data). As postprocessing, we removed non-ASCII characters and several improper symbols from the generated arguments. The fine-tuning took around 16 hours on a GPU Tesla T4.

Argument Generation Models For fine-tuning the generation model, there are various possible combinations of the three constructed graphs and the datasets. Based on initial tests of potentially promising combinations, we decided to address the following models in order to examine the impact of the graphs as well as the data:

1. **GPT-2.** As a baseline, we use the raw GPT-2 model without any fine-tuning or graph usage.
2. **ArgData.** This model is based on fine-tuning GPT-2 using the argumentative texts from Kialo and args.me in our constructed data. No knowledge from the graphs is used here.
3. **AB-ArgData.** Similar to the previous model, but the knowledge of the graphs A and B are encoded into the argumentative texts. Concretely, we combine A and B as follows: First, we compute the intersection of A and B. Then, we add the nodes and edges of A to the resulting intersection subgraph of B, including the nodes of this subgraph as well as their neighbors. Thereby, we reduce the usage of noisy knowledge, preferring knowledge with direct connections.\(^4\)
4. **ABC-ArgData.** Just like the previous model, but we consider the knowledge of graph C in addition to A and B. We compose the graph above and C analog to above. The rationale is here to prefer argumentative knowledge over more general knowledge. The graph C is several orders of magnitude larger than A and B; considering the complete graph of C would thus likely eliminate the impact of A and B.
5. **ABC-FullData.** Analogous to the model before, but here we use the Wikipedia subset of our data in addition to the argumentative one.

In general, those models help investigate the impact of adding one type of information (data or

\(^3\)https://github.com/minimaxir/gpt-2-simple

\(^4\)In other words, we consider the complete graph A, since A is the one with highest precision, and we induce a subset of graph B that is related to A. Our inspections suggested that this subset has much higher precision than the complete graph B.
Multiculturalism is positive for tolerant society.

GPT-2: no guarantee that the world of cultural evolution is going to be one of a kind. in a world where the majority of people are now tolerant, where many people still believe in evolution, we have to accept the world of cultural evolution as being a far more complicated...

ArgData: multiculturalism is a good way to go about making the world a more tolerant place. in the u.s., more than half americans think their country has more tolerance and diversity than other countries...

AB-ArgData: multiculturalism will allow for more tolerant societies. multiculturalism is already a force for good, helping to bring tolerance and diversity to the world. a multicultural society will bring such things as tolerance, kindness, and respect for everyone...

ABC-ArgData: multiculturalism will increase the diversity of the population. the european union eu was created to foster tolerance towards many cultures, but it is still intolerant towards many other cultures...

ABC-FullData: multiculturalism is an accepted part of a multicultural society. the majority of the population of a multicultural society are not religious, not socially or culturally dominant, and do not have political power...

Table 4: Examples of the arguments generated in response to the prompt by each of the evaluated approaches.

| Model          | Args.me | Kialo | Wikipedia |
|----------------|---------|-------|-----------|
| AB-ArgData     | 104,923 | 65,617| –         |
| ABC-ArgData    | 367,697 | 204,651| –         |
| ABC-FullData   | 367,697 | 204,651| 943,070   |

Table 5: Number of relations (knowledge instances) for each of the graph models encoded in the argumentative texts from args.me and Kialo as well as in Wikipedia.

4.2 Manual Evaluation

For evaluation, we generated 400 arguments using the prompts discussed above. Specifically, each model generated 16 arguments for each of the five test topics (80 arguments in total). Table 4 shows some examples of the generated arguments.

Annotation Task The evaluation was done by five workers hired on the freelancing platform, Upwork. The workers were writing experts, with a solid background in argumentation. They had at least 94% job success with more than 40 previous jobs on the platform. Each worker assessed the generated arguments from all models for two test topics, seeing all variants at the same time. Thus, each model was evaluated by two different workers. We paid each worker EUR 140 in total. The average time to complete the task was nine hours.

The assessment of the arguments given their prompts was conducted based on five dimensions:

- Relevance. Does the text comprise content relevant to the given knowledge?
- Argumentativeness. Does the text convey an explicit or implicit pro or con stance towards any topic?
- Content Richness. Does the text contain useful information and cover different aspects?
- Plausibility. Does the text comprise plausible content and does it not contrast with commonsense knowledge?
- Bias. Does the text include any social bias or abusive language?

The first four are adopted from Hua and Wang (2018) and Gretz et al. (2020). We added the last one in light of the observations of Spliethöver and Wachsmuth (2020). The first four dimensions were
Table 6: Manual evaluation: Average scores between 1 (worst) and 3 (best) for the first four dimensions and proportion of generated arguments reported to have bias. The best values are marked bold.

| # | Model               | Relevance | Argumentativeness | Content Richness | Plausibility | Bias |
|---|---------------------|-----------|-------------------|------------------|--------------|------|
| 1 | GPT-2               | 1.80      | 2.23              | 2.11             | 2.33         | 6%   |
| 2 | ArgData             | 1.91      | 2.50              | 2.10             | 2.20         | 13%  |
| 3 | AB-ArgData          | 2.00      | 2.50              | 2.14             | 2.34         | 6%   |
| 4 | ABC-ArgData         | 2.10      | 2.45              | 2.16             | 2.27         | 13%  |
| 5 | ABC-FullData        | 1.85      | 2.26              | 2.10             | 2.04         | 6%   |

scored from 1 to 3 (1 being worst), while the last one was answered with “yes” or “no”.

We directed the workers to consider the length of the argument (100 words) in their assessments. We also asked them to keep in mind that the text should be self-contained; it should not be necessary to see the prompts to understand the text. As regards the argumentativeness dimension, we defined the scores to indicate ‘no stance’ (score 1), ‘mixed stances’ (2), and ‘one stance’ (3) of the generated argument. Unlike previous work, we omitted fluency as a dimension in our evaluation, since all the models are based on GPT-2, which is known to generate mostly fluent text. We manually checked a few samples, though, to confirm the reasonable fluency of the generated arguments.

Results Table 6 shows the resulting scores of all approaches in the manual evaluation. The inter-annotator agreement between the workers is 0.40 in terms of Fleiss’ \( \kappa \).

All models constructed with our data and graphs outperform the raw GPT-2 model in most cases. For relevance, the model with the three graphs and the argumentative data, ABC-ArgData, performs best (2.10), followed by AB-ArgData (2.00). Such results clearly demonstrate the impact of the graphs in controlling the generated arguments. One exception is ABC-FullData, where it seems that using Wikipedia produces some shifts in topics in the generated arguments. Regarding argumentativeness, the models that were developed using the argumentative data achieve the highest score, leaving GPT-2 and ABC-FullData behind. As for content richness, ABC-ArgData reaches the highest scores, marginally higher than AB-ArgData and the other models. In general, all models show comparable performance for this dimension. For plausibility, the score of AB-ArgData is highest, closely followed by GPT-2, though. Despite failing on the other dimensions, GPT-2 apparently generates comparably plausible texts when having argumentation knowledge as prompts.

As regards the last dimension, it seems that the output of all models sometimes conveys bias. However, this dimension appears to be very subjective, as only two workers reported biased arguments at all. Most of the reported arguments are about illegal immigration and multiculturalism. Examples include “the British are a big threat to the idea of multiculturalism” and “The latest attempt to bring the problem under control is the proposal to ban black people from entering the country.”

4.3 Automatic Evaluation

In the automatic evaluation of arguments, we aimed to approximate dimensions from the manual evaluation. On one hand, this was to keep the focus on argumentation-related aspects. On the other hand, it allows for a rough comparison between the manual and the automatic evaluation results. Based on recent computational argumentation technologies, we assessed three dimensions as follows:

- **Relevance.** We computed the overlap between an argument’s words and the prompt’s words, after excluding stop words. To match the manual evaluation scores, we mapped full overlap to 3, partial overlap to 2, and no overlap to 1.

- **Argumentativeness.** We detected the stance of each argument using the approach of Stab et al. (2018), which has been shown to be effective in dealing with arguments from heterogeneous sources, topics, and domains. In particular, we checked the stance (pro or con) for each sentence, considering its topic. We scored the argument with 1 in case no stance is detected, 2 if two different stances are detected (pro and con), and 3 if only one stance is detected.

- **Content Richness.** As we consider an argument to be rich in content if it covers different aspects of a topic, we used the model of Schiller et al. (2021) for identifying aspects in arguments. We then mapped the number of detected aspects to scores heuristically: we
Table 7: The results of the automatic evaluation of the five models on the 400 generated arguments. The highest average score of each dimension is marked bold.

| Model          | Relevance | Argumentativeness | Richness |
|----------------|-----------|-------------------|----------|
| GPT2           | 1.82      | 2.52              | 1.59     |
| ArgData        | 2.26      | 2.70              | 1.94     |
| AB-ArgData     | 2.36      | 2.79              | 2.02     |
| ABC-ArgData    | 2.35      | **2.85**          | **2.10** |
| ABC-FullData   | 2.10      | 2.67              | 2.08     |

gave score 1 to arguments with maximum two aspects, score 2 for three to five aspects, and score 3 for more than five.

Results

Table 7 presents the results of our automatic evaluation.

Again, all models perform better than GPT-2. In terms of relevance, AB-ArgData (2.36) and ABC-ArgData (2.35) are on par. Regarding argumentativeness, ABC-ArgData is the best with an average score of 2.85, and AB-ArgData follows with 2.79. Lastly, for content richness, ABC-ArgData again achieves the highest score (2.10), followed by ABC-FullData and AB-ArgData with 2.08 and 2.02, respectively. The results suggest that ABC-ArgData is the best model overall, followed by AB-ArgData. This emphasizes the impact of encoding the knowledge of the graphs into argumentative data for argument generation.

Comparing the scores of the automatic evaluation to the manual one, we observe rather comparable ranks of the models regarding the three dimensions considered.

4.4 Discussion

Inspecting the arguments generated by the models, we observe that their quality varies depending on the topic of the knowledge (e.g., nuclear energy) and their complexity (single or multiple-relations). We also find that the beginning of a generated argument often has higher quality than the end part. For example, some models start generating relations such as ‘x is positive for y’ instead of a text at the end of the arguments. The reason for this difference in quality could be the minimum length of arguments that we force the model to satisfy. Besides, the arguments have several problems, related to those that occur frequently with neural text generation models, such as duplication, contradicting statements, and topic shifting.

In general, we see that the quality of the automatically generated arguments still not on par with human written arguments. Nevertheless, the experiment results show that our approach for controlling the generated arguments using argumentation knowledge graphs improves the quality.

Still, our approach can be improved in several respects. First, argumentation knowledge graphs, especially those which are constructed automatically, might contain knowledge that is noisy, too specific, very abstract, or difficult to be interpreted without context. While we tried to limit such noise as much as possible (see Section 2.2), more sophisticated noise filtering and a ranking of knowledge based on its quality could be an essential improvement step. Besides, we used the simple method of string matching for finding the graphs’ knowledge in the collected argumentative texts. Advanced methods utilizing semantic similarity could lead to more accurate matching. Moreover, although encoding the knowledge as keyphrases seems a reasonable method, different representations that consider the structure of the knowledge are worth investigating (see Section 3.2). Lastly, since our approach is meant as a proof of concept, we used the small GPT-2 model with the parameters adopted from Gretz et al. (2020). Using a larger model and exploring different sampling methods and parameter settings will probably result in a higher quality of the arguments generated.

5 Related Work

In this section, we outline related studies on argument generation, argumentation knowledge graphs, and graph-to-text generation.

Argument Generation

Different approaches to the generation of arguments, or of components thereof, have been proposed in the last years. To create new claims, Bilu and Slonim (2016) recomposed predicates from existing claims with new topics. El Baff et al. (2019) composed complete arguments from given claims following specific rhetorical strategies based on the theoretical model of Wachsmuth et al. (2018). Unlike these approaches, we make use of neural language models.

Hidey and McKeown (2019) built a sequence-to-sequence model to rewrite claims into opposing claims, and Hua et al. (2019) presented a sophisticated approach that, given a stance on a controversial topic, combines retrieval with neural generation techniques to create full arguments with the opposite stance. Gretz et al. (2020) developed a transformer-based pipeline to generate coherent
and plausible claims, whereas Schiller et al. (2021) proposed a language model that controls argument generation on a fine-grained level for a given topic, stance, and aspect. Lastly, Alshomary et al. (2021) generated belief-based claims, encoding the beliefs via conditional language models.

Most similar to our work are the studies of Gretz et al. (2020) and Schiller et al. (2021). Like us, the former also exploits the power of GPT-2, adding context to the model’s training data. The latter is comparable in that it attempts to steer the generation towards aspect-specific arguments. To the best of our knowledge, however, our approach is the first to employ external knowledge from knowledge graphs for the task of argument generation.

**Argumentation Knowledge Graphs** Besides the argumentation knowledge graph of Al-Khatib et al. (2020), Toledo-Ronen et al. (2016) created an expert stance graph to support stance classification. Gemechu and Reed (2019) encoded the relations between segments of an argument into a graph and demonstrated the graph’s effectiveness for argument mining. In our work, we utilize one of the available graphs, among others, using its knowledge to control the argument generation process.

Closely related to argumentation knowledge, causality graphs gained some attention recently. While general knowledge bases such as ConceptNet (Speer et al., 2017) contain causal knowledge, the causality graph of Heindorf et al. (2020) that we utilized is the largest source of causal knowledge, exceeding others by orders of magnitude.

**Graph-to-Text Generation** In the related area of neural graph-to-text generation, researchers have used various techniques (Song et al., 2018; Koncel-Kedziorski et al., 2019b; Schmitt et al., 2020). Within this area, the approaches most related to ours are those that exploit the usage of knowledge in graphs as input to sequence-to-sequence models (Moryossef et al., 2019) as well as those that make use of large pre-trained language models such as Liu et al. (2021), where the pretrained model BART is augmented by knowledge from a graph for generative commonsense reasoning.

Overall, our work concentrates on the context of argumentation, with an approach to encoding different types of argumentation knowledge into the pretrained model GPT-2 in order to allow for more controlled argument generation.

6 Conclusion

This paper tackles argument generation through the use of argumentation knowledge graphs. We have discussed how to take advantage of different manually and automatically created knowledge graphs to encode knowledge in argumentative texts, and how to utilize these texts to fine-tune GPT-2. Our approach is able to generate high-quality arguments for various inputs, including complex relational knowledge. Besides, we proposed a simple method for evaluating arguments automatically, with results correlating to those observed in the manual evaluation. In our future research, we plan to leverage more sources and evaluate other knowledge encoding methods. Moreover, we will study different directions to illuminate the possible social bias in argument generation methods.

**Ethics Statement**

As this paper presents a computational method for generating arguments automatically, different ethical restrictions deserve discussion.

First, we have used only publicly available, non-personalized sources for our text collection. When crawling data from web platforms, we followed the platforms’ policies, adhering to their usage rules.

Second, although we restricted the sources of our dataset and knowledge graphs to those trustworthy of having high quality, the generated arguments included some undesirable materials, such as abusive language and social bias. To account for these findings, we strongly suggest a postprocessing step to filter out such content when using respective data. Moreover, we explicitly checked for bias in the arguments we generated, as presented.

Arguments are a powerful means for changing people’s stances and impact the attitude of communities. To prevent unethical use, such as generating arguments on controversial topics with specific stances and deploying them on social platforms, we will try to restrict the distribution of the data and code to researchers and academic institutions. This seems necessary since we are aware that there is no guarantee that the generated arguments are always factually correct.

**Acknowledgments**

The first author is supported by the German Federal Ministry of Education and Research (BMBF, 01/S18026A-F) by funding the competence center for Big Data and AI (ScaDS.AI Dresden/Leipzig).
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