Towards an argumentative content search engine using weak supervision

Ran Levy,∗ Ben Bogin,† Shai Gretz,‡ Ranit Aharonov, Noam Slonim
IBM Research
{ranl,boginb,avishaig,ranita,noams}@il.ibm.com

Abstract

Searching for sentences containing claims in a large text corpus is a key component in developing an argumentative content search engine. Previous works focused on detecting claims in a small set of documents or within documents enriched with argumentative content. However, pinpointing relevant claims in massive unstructured corpora, received little attention. A step in this direction was taken in (Levy et al., 2017), where the authors suggested using a weak signal to develop a relatively strict query for claim–sentence detection. Here, we leverage this work to define weak signals for training DNNs to obtain significantly greater performance. This approach allows to relax the query and increase the potential coverage. Our results clearly indicate that the system is able to successfully generalize from the weak signal, outperforming previously reported results in terms of both precision and coverage. Finally, we adapt our system to solve a recent argument mining task of identifying argumentative sentences in Web texts retrieved from heterogeneous sources, and obtain $F_1$ scores comparable to the supervised baseline.

1 Introduction

The arguments raised during a decision making process, will often determine its outcome. A common component in all argument models (e.g., (Toulmin, 2003)) is the claim, i.e. the assertion the argument aims to prove. The problem of automatically detecting claims supporting or contesting a given controversial topic (Levy et al., 2014) is considered a fundamental task in the emerging field of computational argumentation (Lippi and Torroni, 2016; Palau and Moens, 2009). We refer to their definition of a Topic and a Claim; Topic - a short phrase that frames the discussion and Context Dependent Claim - a general, concise statement that directly supports or contests the given Topic (we henceforth use the term claim instead of Context Dependent Claim).

Previous works have focused on detecting claims within a small set of documents related to the topic (Levy et al., 2014), or within documents enriched with argumentative content (Stab and Gurevych, 2014). However, pinpointing relevant claims within massive unstructured corpora, received relatively little attention. While this problem is obviously more challenging, its potential value is also much higher. For a widely discussed topic, one should expect many relevant claims to be mentioned across a widespread set of articles in the given corpus. The remaining issue is to develop a technology to swiftly detect these claims and present the results to potential users, similarly to search engines that retrieve information in response to a query.

A step in this direction was taken in (Levy et al., 2017). They suggested a relatively strict sentence-level query (strict in the sense that it considerably limits the set of potential answers hence reduces the coverage). Their query combines three query parts that must appear in order, with possible gaps between them. The first part requires the sentence to contain the token ‘that’ as it is often a precursor for a claim (e.g. <someone> argued that <claim>). The second query part requires some restriction on the scope of topics the system can handle, and assumes that each topic deals with exactly one concept (denoted

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∗ First three authors contributed equally.
†We will henceforth refer to claims supporting or contesting a given controversial topic as relevant claims.
MC – for main concept) and that this concept has a Wikipedia title (e.g. Affirmative Action). The second part of the query thus restricts the returned sentences to those in which the MC follows the word ‘that’ (possibly with a gap). The third and final query part requires a token from a pre-specified claim lexicon (CL) to appear after the MC (possibly with a gap). The CL lexicon aims to characterize claim sentences (CS) and the process of its creation did not involve any labeled data. Table 1 shows the fifty most indicative tokens from the lexicon. Relying on this formulation led to promising precision results in the challenging task of corpus wide claim detection, albeit with low recall. Specifically, while each of the sentences in Table 2 contains a valid and relevant claim, only $S_1$ satisfies their query; In contrast, $S_2$ satisfies only the first part of the query (‘that’ preceding the MC); $S_3$ satisfies the second part of the query (CL token following the MC); and $S_4$ only mentions the MC. By construction, these latter three sentences, are out of the radar of Levy et al. (2017).

| Example Id | Sentence |
|------------|----------|
| S1 | He believed that nuclear power would become obsolete, to be replaced by clean energy sources. |
| S2 | The author concludes that wind energy has the greatest potential for near-term expansion. |
| S3 | As Buckley writes, “If atheism was unacceptable, superstition and fanaticism were even more so”. |
| S4 | Any form of corporal punishment is barbaric and has no place in a civilized polity. |

Table 1: Fifty most indicative words in the Claim Lexicon (starting from the most indicative)

Table 2: CS examples for the topics ‘We should further exploit nuclear power’, ‘We should further exploit wind power’, ‘Atheism is the only way’ and ‘We should prohibit corporal punishment’. The query items ‘that’, MC and CL are highlighted in boldface.

The main contribution of the current work is to propose a more flexible approach for corpus wide claim detection, that significantly outperforms previous work, in terms of both precision and of coverage. We also release two data sets, one of $\approx 1.5M$ sentences matching the topics in this study, and one of 2,500 sentences predicted by our method, annotated for whether they contain a relevant claim or not.

We use Deep Neural Networks (DNN) trained with weak supervision that stems from different parts of the aforementioned query. Considering the list of 100 MC used by Levy et al. (2017), we first construct two weakly supervised labeled data sets, each composed of two classes. In the first, the weakly-positive class includes all sentences that mention the MC preceded by ‘that’; while the weakly-negative class contains a similar number of sentences that mention the MC without a preceding ‘that’. Our underlying assumption is that the former set will be more enriched with CS (this we first noted in Levy et al., 2014)). However, since these two classes are trivially distinguished via the (non) presence of ‘that’, we train the DNN on the suffixes of the sentences in these data, where the suffix of a sentence is defined as the sentence part immediately following the MC.

Similarly, we construct another data set, in which the weakly-positive class includes all sentences that mention the MC followed by a token from CL; while the weakly-negative class contains a similar number of sentences that mention the MC without a following token from CL. Here as well, to avoid the trivial signal, we train the DNN on the prefixes of the sentences in these data, where the prefix of each sentence is defined as the sentence part immediately following the MC.

The data sets can be downloaded from http://www.research.ibm.com/haifa/dept/vst/debating_data.shtml

\(^2\)The data sets can be downloaded from http://www.research.ibm.com/haifa/dept/vst/debating_data.shtml
The priors for the two positive classes as well as the strict query were estimated in (Levy et al., 2017) by performing a small labeling experiment. We present their results in table 3 in order to demonstrate that the assumptions indeed hold.

| Query Name | Query | Estimated Prior |
|------------|-------|-----------------|
| $q_{MC}$   | $MC$  | 2.4%            |
| $q_{that}$ | $that \rightarrow MC$ | 4.8% |
| $q_{CL}$   | $MC \rightarrow CL$ | Not Estimated |
| $q_{strict}$ | $that \rightarrow MC \rightarrow CL$ | 9.8% |

Table 3: Estimated priors for different queries from (Levy et al., 2017).

Finally, we restrict both datasets to sentences in which the number of suffix (prefix) words is greater than 3. We assume this restriction mostly removes negative examples, and in any case will not convey a lot of information to the DNN in the learning process.

We test the performance of these DNNs over a distinct test set of 50 topics, also from (Levy et al., 2017). However, in contrast to this previous work, we consider a much more relaxed query that only requires the MC to be mentioned in the sentence. Our results clearly indicate that both DNNs were able to generalize and obtain promising precision results, that are further improved when their scores are averaged. That is, combining the predictions of a DNN trained over prefixes of sentences enriched with claims, with those by a DNN trained over suffixes of such sentences, results in a pincer–movement like approach, that successfully pinpoints a wide range of CS in a massive unstructured corpus, while using only weak supervision for training.

2 Related Work

Recently, Wachsmuth et al. (2017) suggested an argument search framework and a corresponding search engine prototype. However, the proposed system relies on arguments crawled from dedicated resources that suggest pre–written arguments for various topics, and hence, is only relevant for topics covered in these resources, and cannot be used directly over unstructured textual data. Stab et al. (2018) tackled the argument mining task in heterogeneous texts retrieved by Google search when queried with a controversial topic. They show that it is feasible to annotate the retrieved documents via crowd-sourcing and to use these labels in order to build a supervised learning system that finds arguments in the given documents. Similar to our work, sentences are treated in isolation (ignoring the document context). The only work we are aware of that tackles corpus wide claim detection, is the work by (Levy et al., 2017). Here, we demonstrate how this work can be leveraged to define weak signals for training DNNs to obtain significantly greater performance.

Several works used DNN to tackle a variety of computational argumentation tasks, such as argument mining (Eger et al., 2017), predicting argument convincingness (Habernal and Gurevych, 2016), detecting context dependent claims and evidence (Laha and Raykar, 2016) and attack and support relations between arguments (Cocarascu and Toni, 2017). However, these works used the fully–supervised learning paradigm, which is inherently demanding, especially in the context of argument mining where obtaining labeled data is notoriously difficult (Aharoni et al., 2014). In addition, Al-Khatib et al. (2016) used a distant supervision approach trained over debate portals’ data, to develop a classifier for argumentative texts stored in these portals. To the best of our knowledge, the present work is the first to demonstrate the value of DNN trained solely with weak supervision (Hearst, 1992) in this challenging field.

For a good exposition on the field of argument mining refer to (Lippi and Torroni, 2016). Some notable works include (Palau and Moens, 2009) who first suggested the argument mining task, (Levy et al., 2014; Rinott et al., 2015) who focused on mining claims/evidence in the context of a user given controversial topic and several works related to specific text genres such as student essays (Stab and Gurevych, 2014), legal documents (Wyner et al., 2010; Moens et al., 2007; Grabmair et al., 2015), user comments on proposed regulations (Park and Cardie, 2014) and newspaper articles (Feng and Hirst, 2011).
3 Method

3.1 Setup and pre-processing
We follow the setup and pre-processing described in (Levy et al., 2017) – see appendix for details. We consider the same train and test sets, consisting of 100 and 50 topics respectively. Next, we prepared a sentence–level index from the Wikipedia May 2017 dump, and used a simple Wikification tool (to be described in a separate publication) to focus our attention on sentences that mention the MC. Filtering out sentences that mention a location/person named entity using Stanford NER (Finkel et al., 2005), after the MC, results in an average of \( \approx 10K \) sentences per MC.

3.2 Claim sentence queries and weak labels
The basic query we start with, denoted \( q_{MC} \), only requires that the MC will appear in the sentence. For the 150 topics of this study, we retrieve a total of \( \approx 1.5M \) sentences matching \( q_{MC} \) (Table 4), which we release as a data set to enhance future research. Next, we consider the query \( q_{that} \), which retrieves all sentences in which the token ‘that’ precedes the MC (cf. \( S1 \) and \( S2 \) in Table 2). There are \( \approx 1,100 \) such sentences per topic (Table 4). Aiming to increase the prior of CS in the weak–positive set, for training the network, we focus on the subset of these sentences in which the token ‘that’ immediately precedes the MC. As a weak–negative set we consider a similar number of sentences, with similar length distribution, selected at random from the \( q_{MC} \) sentences with the additional requirement of not having ‘that’ before the MC. As explained in section 1, the corresponding DNN, termed \( DNN_{suff} \), is trained only on the sentence suffixes.

| Query Name | Query | # Sentences Per Topic |
|------------|-------|-----------------------|
| \( q_{MC} \) | MC | 9,947 |
| \( q_{that} \) | that \( \rightarrow \) MC | 1,073 |
| \( q_{CL} \) | MC \( \rightarrow \) CL | 793 |
| \( q_{strict} \) | that \( \rightarrow \) MC \( \rightarrow \) CL | 164 |

Table 4: Queries used to construct weak labels. # Sentences Per Topic is averaged over the 150 topics used in this study. \( q_{strict} \) is added for reference and was not used in training the networks.

Similarly, we consider the query \( q_{CL} \), which retrieves all sentences in which the MC is followed by a token from CL, e.g., sentences \( S1 \) and \( S3 \) in Table 2. Again, these sentences as well are expected to be relatively enriched with claims. In Table 4 we see that on average we have \( \approx 790 \) such sentences per topic. As a weak–negative set we consider a similar number of sentences, with similar length distribution, selected at random from the \( q_{MC} \) sentences with the additional requirement of not having a CL token after the MC. Again, the corresponding DNN, denoted by \( DNN_{pref} \) is trained only on the sentence prefixes.

Table 5 lists examples of sentences in the weak–positive and weak–negative sets used to train the networks. The part “seen” by the relevant network appears in bold, where by an anecdotal examination it is indeed possible to identify a signal in the positive sets. Table 6 summarizes the characteristics of the two datasets used to train the networks.

3.3 DNN System
For both \( DNN_{suff} \) and \( DNN_{pref} \), we use a Bi-LSTM architecture with self-attention (Yang et al., 2016). The networks were trained on sentences retrieved for 70 of the 100 train–set topics, where sentences retrieved from the other 30 train–set topics (heldout set) were used to optimize hyper-parameters. We used Adam optimizer (Kingma and Ba, 2014) over the cross-entropy loss. The best model was

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3 The set of 100 topics was termed dev set in their work because there was no training involved.
4 A Wikification tool allows retrieving sentences that mention the topic explicitly, as well as sentences which use a different surface form, as in S2 in Table 2 (wind energy surface-form linked to the wind power concept).
There is no good evidence that organic food tastes better than its non-organic counterparts.

Today it is known for its remoteness, its somewhat “alternative” atmosphere, organic food production, and its pioneering use of wind power.

Fermi did not believe that atomic bombs would deter nations from starting wars, nor did he think that the time was ripe for world government.

In particular, fission products do not themselves undergo fission, and therefore cannot be used for nuclear weapons.

Table 5: Examples from the positive and negative sets of $DNN_{suff}$ and $DNN_{pref}$ for the topics “Organic Food” and “Nuclear weapon”. The respective prefix/suffix appears in bold.

| Network | Positive/Negative | Sentence |
|---------|-------------------|----------|
| $DNN_{suff}$ | Positive | There is no good evidence that organic food tastes better than its non-organic counterparts. |
| $DNN_{suff}$ | Negative | Today it is known for its remoteness, its somewhat “alternative” atmosphere, organic food production, and its pioneering use of wind power. |
| $DNN_{pref}$ | Positive | Fermi did not believe that atomic bombs would deter nations from starting wars, nor did he think that the time was ripe for world government. |
| $DNN_{pref}$ | Negative | In particular, fission products do not themselves undergo fission, and therefore cannot be used for nuclear weapons. |

Table 6: Characteristics of the two datasets used to train the networks. Note that the data for the suffix network is much smaller because of the restriction to sentences in which the token ‘that’ immediately precedes the MC.

| Network | Positive sentences | Negative sentences | Part of sentence used by the network | Size of data |
|---------|--------------------|--------------------|-------------------------------------|-------------|
| $DNN_{suff}$ | that → MC | MC without preceding ‘that’ | following the MC | 11,624 |
| $DNN_{pref}$ | MC → CL | MC without a following CL token | preceding the MC | 132,856 |

We trained with a dropout of 0.15, using a single dropout mask across all time-steps as proposed by (Gal and Ghahramani, 2016), one LSTM layer with a cell size of 128, and an attention layer of size 100. Words are represented using the 300 dimensional GloVe embeddings (Pennington et al., 2014). Inference is performed for any $q_{MC}$ sentence by averaging the $DNN_{suff}$ score of its suffix with the $DNN_{pref}$ score of its prefix.

We used the heldout set to determine early stopping and to optimize the following hyper-parameters (each parameter was optimized independently): Number of layers (1/2), LSTM cell size (64/128/256/512), attention FF size (50/100/200) and dropout rate (0/0.05/0.1/0.15/0.2/0.25/0.3/0.35).

4 Data for evaluation

We labeled via crowd the top 50 predicted sentences for each of the 50 test-set topics, taking the majority vote of at least 10 workers. The guidelines are presented in figure 1. The inference is applied to all sentences containing the MC (matching $q_{MC}$), and hence there are always 50 predictions, that are all released along with their manual evaluation. We also label in the same manner the predictions of the system described in (Levy et al., 2017)\(^5\). There, since all predictions must match $q_{strict}$, for some topics there are less than 50 predictions. In those cases, we label all predictions.

This paper focuses on retrieving claim sentences, however, we have found that it is easier for the crowd workers to label a sentence if the phrase suggested to be the claim is highlighted. For this reason, we used an internal boundary detection component and applied it to all system versions (including the re-implementation baseline of (Levy et al., 2017)). The rest of the labeling process was done similarly to (Levy et al., 2017). Each sentence was labeled by 10-15 crowd workers per row via the Figure–Eight platform\(^6\). We used the MACE de-noising tool (Hovy et al., 2013) to filter labels before computing Cohen’s Kappa coefficient. We averaged the Kappa coefficient across all worker pairs with at least 50 joint labeled instances. Using a threshold of 0.9 (i.e. keeping 90% of the labels) the Kappa was 0.58.

\(^5\)We re-implemented their system since since we used a more recent Wikipedia dump and a different Wikification tool. The results we obtained are very close to the reported results.

\(^6\)https://www.figure-eight.com/ (previously known as CrowdFlower)
5 Results

To evaluate the performance of the network, we employ two sets of experiments. In the first we use the test-set topics in a manner similar to (Levy et al., 2017). In the second, we test our network on the UKP Sentential Argument Mining Corpus released in (Stab et al., 2018). Note that the UKP data is more inline with our goal than other argument mining tasks as it separates between sentences that support/contest a given topic from sentences that don’t. A major difference between the UKP data and our test set is the source from which the sentences were taken – while we used Wikipedia, the UKP data comes from various sources, and hence it would test how well our approach generalizes to other text genres. Another important difference is in the definition of positive examples - we consider sentences containing relevant claims as positive, whereas they require that a sentence contain some supporting evidence or reasoning. The results on our test set are presented in subsection 5.1 and the results on the UKP data are presented in subsection 5.2.

5.1 Results on the Test Set

Figure 2 depicts the average number of CS (i.e., true positives) retrieved per the top \( K = 10, 20, 50 \) predictions. Both \( D N N_{\text{pref}} \) and \( D N N_{\text{suff}} \) seem to generalize well from the weak signal and provide comparable results to (Levy et al., 2017). More importantly, using the average score (DNN) yields the best performance, consistently outperforming (Levy et al., 2017) (with \( p \)-value < 0.005 for \( K = 20, 50 \) based on a two-tailed Wilcoxon test). The gap is most prominent for \( K = 50 \), where the DNN yields \( \approx 30\% \) more CS compared to the non–learning system that used a strict query with limited recall.

A major question is whether the learned system is able to generalize from the weak labels and identify CS that do not match the weak queries we started with. By construction, all sentences retrieved by the (Levy et al., 2017) system, match \( q_{\text{strict}} \). From Table 7, we see that although the DNN system trained on sentences matching \( q_{\text{hat}} \) or \( q_{\text{CL}} \) or both, 28% of the 2500 sentences predicted by the system, do not match either. Sentence \( S4 \) in Table 2 is an example of such a predicted sentence. The precision on those sentences, that are only known to contain the MC, is still considerably high – 0.22, and in fact comparable...
to the precision achieved in the restricted, low-recall system of (Levy et al., 2017). These results suggest that the DNN captures some general characteristics of CS, that are not limited to sentences that satisfy the two weak-signal queries we started with, \(q_{\text{that}}\) and \(q_{\text{CL}}\). In addition, the precision on sentences containing one or both of the weak signals is even higher. Specifically, the precision on the subset of sentences matching \(q_{\text{strict}}\) is 0.42, a factor of two compared to the precision of (Levy et al., 2017) on this set of sentences. Thus, overall we were able to increase the potential recall from the restricted set of sentences matching \(q_{\text{strict}}\) to the full set of \(q_{\text{MC}}\) sentences, while also increasing the precision of the predictions from 0.23 to 0.3 (see the column \(q_{\text{MC}}\)).

| Measure | System | \(q_{\text{strict}}\) | \(q_{\text{that}}\) | \(q_{\text{CL}}\) | \(q_{\text{MC}}\) |
|---------|--------|---------------------|-------------------|----------------|----------------|
| Percent | Levy   | 100 | 0 | 0 | 0 | 100 |
| DNN     | 30 | 26 | 16 | 28 | 100 |
| Precision | Levy | 0.23 | NA | NA | NA | 0.23 |
| DNN     | 0.42 | 0.32 | 0.22 | 0.22 | 0.30 |

Table 7: Distribution and precision of predictions. \(q_{\text{that}}^*\): matches \(q_{\text{that}}\) but not \(q_{\text{CL}}\); \(q_{\text{CL}}^*\): matches \(q_{\text{CL}}\) but not \(q_{\text{that}}\); \(q_{\text{MC}}^*\): matches \(q_{\text{MC}}\), but not any of the other queries. Percent: out of the top 50 (or all if less available) predicted sentences matching the query. Precision: Precision of the corresponding candidates, calculated per topic, and averaged over test topics.

5.2 Results on the UKP Sentential Argument Mining Corpus

The UKP Sentential Argument Mining Corpus (Stab et al., 2018) contains a total of 25,492 labeled sentences (11,139 argumentative, 14,353 non-argumentative), divided to train (70%), validation (10%), and test sets (20%). The sentences are associated with one of 8 controversial topics – abortion, cloning, death penalty, gun control, marijuana legalization, minimum wage, nuclear energy and school uniforms – and were derived from the top 50 results of a Google query for the topic name, thus representing various genres and text types.
Adapting to the UKP dataset

In order to evaluate our method on the UKP dataset we had to adapt it to sentences that do not necessarily contain the MC. In our formulation, the MC was used as a natural point to divide the sentence into its prefix and suffix, which were then used by the appropriate networks. To overcome this difference, we applied $DNN_{\text{pref}}$ ($DNN_{\text{pref}}$) to all possible suffixes (prefixes) and used the maximal score.

For a sentence $S$ comprised of $n$ words, $w_1, w_2, ..., w_n$, we define,

$$DNN'_{\text{suff}}(S) = \max_{i=1..n} DNN_{\text{suff}}(w_i, ..., w_n)$$

$$DNN'_{\text{pref}}(S) = \max_{i=0..n-1} DNN_{\text{pref}}(w_1, ..., w_n-i)$$

The adapted scores may still be at a disadvantage because without the MC we don’t have a way to select sentences that are more related to the topic. For this reason we add a similarity score $Score_{w2v}$ which is computed by taking the maximal word2vec (Mikolov et al., 2013) similarity of a word in the topic against all words in the sentence and then averaging across the words of the topic. More formally, for a topic $T$ comprised of $k$ words, $t_1, ..., t_k$,

$$Score_{w2v}(S) = \text{avg}_{i=1..k} \max_{j=1..n} \text{word2vec}(t_i, w_j)$$

Finally, we define,

$$DNN'_{\text{suff},w2v} = \text{avg}(DNN'_{\text{suff}}, Score_{w2v})$$

$$DNN'_{\text{pref},w2v} = \text{avg}(DNN'_{\text{pref}}, Score_{w2v})$$

We employ the same setup that was used by (Stab et al., 2018) for the cross topic evaluation, in which the train set is comprised of the train part of all topics except for the tested topic. We use the training set only to tune the threshold from which we predict the positive class. To do so, we run the different DNN methods on the train set, compute the $F_1$ over all sentences, and choose the score that maximizes the $F_1$. This score is then used in the test set as the threshold that determines whether the network predicts a positive or not. Overall, this tuning was done 8 times, one for each train set induced by the left-out test topic.

Evaluation

The results are shown in table 8. Interestingly, our system achieves comparable results to the state of the art in the Accuracy and $F_1$ measures but without using human labels for training and without training on multiple text genres. These results also demonstrate the ability of the proposed method to generalize to topics that are not characterized by a single MC or that such a concept was not provided by the user. Note, the results reflect that our system and the baseline operate at different points on the precision/recall curve, choosing a different compromise between precision and recall. This is not surprising, given the choice of tuning the $F_1$ measure on the train set, however, it makes the comparison less obvious.

| Method            | Accuracy | $F_1$  | Precision | Recall |
|-------------------|----------|--------|-----------|--------|
| UKP               | 0.69     | 0.66   | 0.75      | 0.52   |
| $DNN_{\text{suff}}$ | 0.57     | 0.65   | 0.51      | 0.90   |
| $DNN'_{\text{suff},w2v}$ | 0.67     | 0.69   | 0.59      | 0.83   |

Table 8: Results of the cross topic evaluation on the UKP dataset (averaged across the 8 topics). UKP method stands for the best supervised results reported in (Stab et al., 2018). From the networks combined with $w2v$ the $DNN'_{\text{suff},w2v}$ performed best and is the one presented here.

It should be noted that the lower precision of our method may be explained by the different assumption on what an argumentative sentence is. Whereas Stab et al. (2018) reject sentences that contain claims but provide no evidence or reasoning, our network was designed to identify claims regardless of the
existence of a surrounding argument. Indeed, as mentioned in section 6.2, by sampling 50 false-positives we found that in 25% of the cases they contained relevant claims but with no evidence or reasoning.

6 Error Analysis

6.1 Test Set - 50 Topics

We analyzed the top 50 labeled predictions over three test topics for which the performance was above/near/below average (table 9).

| Topic Text                                | Main Concept | Pos@50 |
|-------------------------------------------|--------------|--------|
| We should further exploit wind power      | Wind power   | 29     |
| Private education brings more good than harm | Private school | 13     |
| We should protect whistleblowers          | Whistleblower| 9      |

Table 9: Test topics chosen for error analysis.

Each sentence rejected by the labelers was assigned one of the following types: Factual – a sentence with no argumentative content, that merely states a fact; Different Topic – a sentence that contains a claim for a different topic; Other – an assortment of problems such as bad sentence split, missing context, etc; and finally Accept – a sentence that should have been accepted by the labelers. The two main types of errors were Factual and Different topic, each accounting for 35% of the analyzed errors. The Accept type accounted for 18% of the rejected sentences, though this high number was mostly due to the Whistleblowers topic. We suspect that many such sentences were rejected because of bad claim boundary choices by the system \(^7\). Table 10 shows examples from the topic “Private education brings more good than harm”.

| Error Type   | Sentence                                                                 |
|--------------|--------------------------------------------------------------------------|
| Different Topic | Changes in private school enrollment is not a likely contributor to any changes in schools segregation patterns during that time. |
|              | In 2014 Hunt proposed that private schools should be required to form “partnerships” with local state schools if they wanted to keep their charitable status. |
| Factual      | Before enrolling the children, however, Mr. Brar ensured that the total cost of private school tuition would not exceed $10,000. |
|              | The IRS announced in 1970 that private schools with racially discriminatory admissions policies would no longer receive tax exemptions |
| Accept       | Coaches were concerned that the private schools were winning a disproportionate amount of conference titles and had several unfair advantages. |
| Other*       | It is clear that affording private education is a mere fantasy for these families. |

Table 10: Examples of sentences from the topic ‘Private education brings more good than harm’. The sentences are split according to their assigned error type. * The example for the Other type was rejected because of a missing context – it is hard to judge this example without resolving the reference to “these families”

6.2 Test Set - UKP Dataset

We analyzed 50 random sentences from the UKP test set labeled as non-argumentative, on which the score of the $DNN^F_{w^2t}$ network was higher than 0.9 (the average threshold obtained by tuning $F_1$ was 0.65). We add the following error type to the list above: No Reasoning – a sentence containing a claim with no supporting evidence or reasoning. The most frequent type of error was Factual, accounting

\(^7\) We used a claim boundary component (Levy et al., 2014) on top of all systems in order to simplify the labeling task. This came at a cost of some CS being rejected due to errors in the boundary component.
for about 33% of the errors. The No Reasoning type accounted for about 25% of the errors, similar to the Different Topic type. Table 11 shows examples of No Reasoning sentences. These sentences contain text boundaries that are relevant claims, e.g., the boundary *the life in the womb is not human* in the first sentence, and thus are typical to sentences that our network was trained to find.

| Topic          | Sentence                                                                 |
|---------------|--------------------------------------------------------------------------|
| abortion      | *A question for those who believe in abortion, and that the life in the womb is not human.* |
| death penalty | *We need stricter laws and swift death penalty.*                          |
| minimum wage  | *Myth: Raising the minimum wage will only benefit teens.*                |
| marijuana     | *A small share of opponents (7%) say that while the recreational use of marijuana should be illegal, they do not object to legalizing medical marijuana.* |

Table 11: Examples of sentences marked as No Reasoning from the UKP test set. The phrases marked in boldface are the suggested claim boundaries according to our analysis.

7 Discussion and Future Work

This work aims at making the first steps towards a search engine for argumentative content, by focusing on the problem of corpus wide claim detection. A variety of argument theories have been proposed throughout the years, which all agree on the importance of one argument component – the claim. Thus, properly addressing the problem of corpus wide claim detection seems like a key component in developing a full fledged argument search engine. Such an engine could add massive amounts of data to argument networks such as the world wide argument web (Rahwan et al., 2007), and further enhance decision processes in various ways. Using a similar methodology for evidence detection would be a natural way to push the boundary of existing work, e.g., (Rinott et al., 2015) from considering a pre-selected list of articles to searching full corpora. To the best of our knowledge this is the first work using weak supervision to train DNNs for argument mining, demonstrating the potential of this coupling in the field.

Two directions for future work could increase the precision and coverage of our system. For increasing precision, we intend to employ a supervised approach, using labels on top of predictions from the weak-supervision approach, as it may help reach a reasonable prior of positive examples before starting the labeling effort. For the coverage, we intend to explore the same approach on top of sentences which do not necessarily contain the MC. This direction is challenging since it requires integrating a method for identifying whether a sentence is related to the topic, and would need to score sentences in which the prior for a claim is even lower.

During the error analysis on the ‘Wind power’ topic, we encountered the following high-scoring sentence – “*When Scratchy suggests that wind power is cheap and safe, Itchy chops Scratchy’s head off with the blades of a wind turbine.*”. On the one hand, Scratchy raises a legitimate claim, and on the other hand, Scratchy is a fictional character from the TV show The Simpsons. The example demonstrates a phenomenon that may be exasperated when moving from argument mining on pre-selected high-quality documents to mining large (possibly heterogeneous) text corpora – the phenomenon of claims made by unreliable sources. In extreme cases the claims made by such parties may be ridiculous or offensive and a practical search engine would need to detect and remove such claims.
Appendix A  Index and Preprocessing

We processed the Wikipedia dump from May 1st, 2017. We applied text cleaning and sentence splitting using OpenNlp Sentence Detector\(^8\) and an internal Wikification tool to wikify each sentence\(^9\). Starting from 5.4M articles, the sentence level index contains approximately 102M sentences. The inverted index along with the support for queries that mix surface form tokens with Wiki concepts was implemented as in (Levy et al., 2017).

We annotated the sentences retrieved by all queries using Stanford NER (Finkel et al., 2005), and removed sentences with a person/location entity after the MC (e.g., the sentence “Yan warned Li that the Nationalist cause was doomed unless Li went to Guangdong” for the topic “Nationalism does more harm than good” would be removed). This filter is motivated by our goal of retrieving general claim sentences for the topic, assuming that claims about specific entities are less interesting for potential users.

Appendix B  Topics and Folds

The list of 150 topics is taken from (Levy et al., 2017) and split to dev/test in the same manner. Since here we use a learning system, we further split the dev set into a train set of 70 topics and a heldout set of 30 topics which was used to decide when to stop the learning. Tables 12 and 13 show the train topics and tables 14 and 15 show the topics of the heldout and test sets respectively.

Appendix C  Released Data

We release two datasets, one containing \(\approx 1.5M\) sentences matching the topics in this study based on the \(q_{MC}\) query, and one containing 2,500 sentences predicted by our network and annotated for whether they contain a relevant claim or not (top 50 predictions across the 50 topics in the test set)\(^{10}\). The \(q_{MC}\) dataset can be found in the attached \(q_{mc}\_train.csv\), \(q_{mc}\_heldout.csv\) and \(q_{mc}\_test.csv\) files, according to the topics split used in the learning/evaluation process. A detailed description of this dataset appears in the readme\(_{mc}\_queries.txt\) file. The system prediction dataset is in the test\(_{set}.csv\) file with a corresponding description in the readme\(_{test}\_set.txt\) file.

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\(^8\)http://opennlp.apache.org/
\(^9\)To be described in a separate publication.
\(^{10}\)The datasets can be downloaded from http://www.research.ibm.com/haifa/dept/vst/debating_data.shtml
| #  | Id  | Topic Text                                                                 | Main Concept                              |
|----|-----|----------------------------------------------------------------------------|-------------------------------------------|
| 1  | 1   | We should ban the sale of violent video games to minors                    | Video game controversies                  |
| 2  | 2   | We should legalize doping in sport                                           | Doping in sport                            |
| 3  | 3   | We should ban boxing                                                       | Boxing                                    |
| 4  | 4   | We should abolish intellectual property rights                              | Intellectual property                     |
| 5  | 5   | We should protect endangered species                                        | Endangered species                        |
| 6  | 6   | Operation Cast Lead was justified                                          | Gaza War (2008-09)                        |
| 7  | 7   | Tower blocks are advantageous                                               | Tower block                               |
| 8  | 8   | Private universities bring more good than harm                              | Private university                         |
| 9  | 9   | We should disband ASEAN                                                    | Association of Southeast Asian Nations    |
| 10 | 10  | The free market brings more good than harm                                  | Free market                               |
| 11 | 11  | We should ban child actors                                                 | Child actor                               |
| 12 | 12  | Religion does more harm than good                                           | Religion                                  |
| 13 | 13  | We should ban cosmetic surgery                                              | Plastic surgery                           |
| 14 | 14  | Same sex marriage brings more good than harm                                | Same-sex marriage                         |
| 15 | 15  | Reality television does more harm than good                                 | Reality television                         |
| 16 | 16  | Internet censorship brings more good than harm                              | Internet censorship                       |
| 17 | 17  | Socialism brings more harm than good                                        | Socialism                                 |
| 18 | 18  | We should ban beauty contests                                               | Beauty pageant                            |
| 19 | 19  | We should adopt vegetarianism                                               | Vegetarianism                             |
| 20 | 20  | We should adopt libertarianism                                              | Libertarianism                            |
| 21 | 21  | The internet brings more harm than good                                     | Internet                                  |
| 22 | 22  | Science is a major threat                                                  | Science                                   |
| 23 | 23  | Suicide should be a criminal offence                                        | Suicide                                   |
| 24 | 24  | Nationalism does more harm than good                                        | Nationalism                               |
| 25 | 25  | The atomic bombings of Hiroshima and Nagasaki were justified                | Atomic bombings of Hiroshima and Nagasaki |
| 26 | 26  | Casinos bring more harm than good                                          | Casino                                    |
| 27 | 27  | We should lower the age of consent                                         | Age of consent                            |
| 28 | 28  | We should abolish standardized tests                                       | Standardized test                         |
| 29 | 29  | We should ban extreme sports                                               | Extreme sport                             |
| 30 | 30  | The alternative vote is advantageous                                       | Instant-runoff voting                     |
| 31 | 31  | Illegal immigration brings more harm than good                              | Illegal immigration                       |
| 32 | 32  | We should subsidize renewable energy                                        | Renewable energy                          |
| 33 | 33  | We should end daylight saving times                                         | Daylight saving time                      |
| 34 | 34  | We should further exploit geothermal energy                                 | Geothermal energy                         |
| 35 | 35  | Assisted suicide should be legalized                                        | Assisted suicide                          |
| 36 | 36  | Security hackers do more harm than good                                     | Hacker (computer security)                |
| 37 | 37  | We should disband the United Nations                                       | United Nations                            |
| 38 | 38  | We should ban hate sites                                                   | Hate speech                               |
| 39 | 39  | We should privatize future energy production                               | Energy development                        |
| 40 | 40  | Child labor should be legalized                                             | Child labour                              |
| 41 | 41  | The paralympic games bring more harm than good                              | Paralympic Games                         |
| 42 | 42  | Chain stores bring more harm than good                                      | Chain store                               |
| 43 | 43  | We should subsidize Habitat for Humanity International                      | Habitat for Humanity                      |
| 44 | 44  | We should subsidize public art                                             | Public art                                |
| 45 | 45  | IKEA brings more harm than good                                             | IKEA                                      |
| 46 | 46  | We should ban online advertising                                           | Online advertising                        |
| 47 | 47  | Mixed-use development is beneficial                                        | Mixed-use development                     |
| 48 | 48  | We should ban Greyhound racing                                             | Greyhound racing                          |
| 49 | 49  | The Israeli disengagement from Gaza brought more harm than good            | Israeli disengagement from Gaza           |
| 50 | 50  | We should not subsidize single parents                                      | Single parent                             |

Table 12: Train topics 1-50
| # | Id | Topic Text                                                                 | Main Concept                        |
|---|----|----------------------------------------------------------------------------|-------------------------------------|
| 51 | 51 | We should ban private military companies                                  | Private military company            |
| 52 | 52 | Coaching brings more harm than good                                        | Coaching                            |
| 53 | 53 | We should abandon disposable diapers                                       | Diaper                              |
| 54 | 54 | PayPal brings more good than harm                                          | PayPal                              |
| 55 | 55 | The Internet archive brings more harm than good                            | Internet Archive                    |
| 56 | 56 | The 2003 invasion of Iraq was justified                                    | 2003 invasion of Iraq              |
| 57 | 57 | Virtual reality brings more harm than good                                 | Virtual reality                     |
| 58 | 58 | Internet cookies bring more harm than good                                 | HTTP cookie                         |
| 59 | 59 | Magnet schools bring more harm than good                                   | Magnet school                       |
| 60 | 60 | The right to strike brings more harm than good                             | Strike action                       |
| 61 | 61 | We should subsidize student loans                                          | Student loan                        |
| 62 | 62 | We should abandon Youtube                                                 | YouTube                             |
| 63 | 63 | Ecotourism brings more harm than good                                      | Ecotourism                         |
| 64 | 64 | Academic freedom is not absolute                                           | Academic freedom                    |
| 65 | 65 | Homeschooling should be banned                                             | Homeschooling                       |
| 66 | 66 | We should abolish the US Electoral College                                | Electoral College (United States)  |
| 67 | 67 | Generic drugs should be banned                                             | Generic drug                        |
| 68 | 68 | We should fight global warming                                            | Global warming                      |
| 69 | 69 | We should fight for Quebecan Independence                                  | Quebec sovereignty movement         |
| 70 | 70 | We should subsidize newspapers                                             | Newspaper                           |

Table 13: Train topics 51-70

| # | Id | Topic Text                                                                 | Main Concept                        |
|---|----|----------------------------------------------------------------------------|-------------------------------------|
| 1  | 71 | The freedom of speech is not absolute                                      | Freedom of speech                   |
| 2  | 72 | We should criminalize blasphemy                                            | Blasphemy                           |
| 3  | 73 | Holocaust denial should be a criminal offence                              | Holocaust denial                    |
| 4  | 74 | Television does more harm than good                                        | Television                          |
| 5  | 75 | We should subsidize higher education                                       | Higher education                    |
| 6  | 76 | We should ban organic food                                                 | Organic food                        |
| 7  | 77 | Urbanization does more harm than good                                      | Urbanization                        |
| 8  | 78 | We should adopt direct democracy                                           | Direct democracy                    |
| 9  | 79 | We should ban lotteries                                                    | Lottery                             |
| 10 | 80 | We should close the Guantanamo Bay detention camp                          | Guantanamo Bay detention camp       |
| 11 | 81 | We should abandon the insanity plea                                       | Insanity defense                    |
| 12 | 82 | We should protect coral reefs                                               | Coral reef                          |
| 13 | 83 | We should disband NASA                                                     | NASA                                |
| 14 | 84 | We should abolish nuclear weapons                                          | Nuclear weapon                      |
| 15 | 85 | We should cancel the speed limit                                           | Speed limit                         |
| 16 | 86 | Randomized controlled trials bring more harm than good                     | Randomized controlled trial         |
| 17 | 87 | Anarchism brings more good than harm                                       | Anarchism                           |
| 18 | 88 | We should subsidize public service broadcasters                            | Public broadcasting                 |
| 19 | 89 | We should ban labor organizations                                          | Trade union                         |
| 20 | 90 | Pride parades bring more harm than good                                    | Pride parade                        |
| 21 | 91 | Paternity leave brings more harm than good                                  | Parental leave                      |
| 22 | 92 | Tabloid journalism brings more harm than good                               | Tabloid journalism                  |
| 23 | 93 | We should disband UNESCO                                                   | UNESCO                              |
| 24 | 94 | We should disband the National Rifle Association                          | National Rifle Association          |
| 25 | 95 | Second Life brought more harm than good                                    | Second Life                         |
| 26 | 96 | Economic sanctions bring more harm than good                               | Economic sanctions                  |
| 27 | 97 | Vietnam War was justified                                                  | Vietnam War                         |
| 28 | 98 | Animal slaughter is not justified                                           | Animal slaughter                    |
| 29 | 99 | We should raise the corporate tax                                           | Corporate tax                       |
| 30 | 100| Division of labor is a major threat                                       | Division of labour                  |

Table 14: Heldout topics
| #  | Id  | Topic Text                                      | Main Concept         |
|----|-----|-----------------------------------------------|----------------------|
| 1  | 101 | Affirmative action brings more good than harm | Affirmative action   |
| 2  | 102 | We should ban gambling                        | Gambling             |
| 3  | 103 | We should abolish the monarchy                 | Monarchy             |
| 4  | 104 | Atheism is the only way                        | Atheism              |
| 5  | 105 | We should further exploit wind power           | Wind power           |
| 6  | 106 | We should legalize polygamy                     | Polygamy             |
| 7  | 107 | We should further exploit hydroelectric dams   | Hydroelectricity     |
| 8  | 108 | We should privatize water supply               | Water supply         |
| 9  | 109 | We should legalize prostitution                 | Prostitution         |
| 10 | 110 | Zoos bring more harm than good                 | Zoo                  |
| 11 | 111 | Private education brings more good than harm   | Private school       |
| 12 | 112 | Recall elections are beneficial                | Recall election      |
| 13 | 113 | We should further exploit nuclear power        | Nuclear power        |
| 14 | 114 | We should abolish temporary employment         | Temporary work       |
| 15 | 115 | Surrogacy should be banned                     | Surrogacy            |
| 16 | 116 | Progressive tax is beneficial                  | Progressive tax      |
| 17 | 117 | We should ban alcoholic beverages              | Alcoholic drink      |
| 18 | 118 | We should ban abortions                        | Abortion             |
| 19 | 119 | Astrology brings more harm than good           | Astrology            |
| 20 | 120 | Embryonic stem cell research brings more good  | Embryonic stem cell  |
| 21 | 121 | We should abolish the Olympic Games            | Olympic Games        |
| 22 | 122 | We should end athletic scholarships            | Athletic scholarship |
| 23 | 123 | Social media does more harm than good          | Social media         |
| 24 | 124 | We should disband the United Nations Security Council | United Nations Security Council |
| 25 | 125 | We should legalize insider trading             | Insider trading      |
| 26 | 126 | We should prohibit hydraulic fracturing        | Hydraulic fracturing |
| 27 | 127 | We should prohibit corporal punishment         | Corporal punishment  |
| 28 | 128 | We should disband NATO                        | NATO                 |
| 29 | 129 | We should abolish the two-party system         | Two-party system     |
| 30 | 130 | Capital punishment brings more harm than good  | Capital punishment   |
| 31 | 131 | We should abolish term limits                  | Term limit           |
| 32 | 132 | We should protect whistleblowers               | Whistleblower        |
| 33 | 133 | Twitter brings more harm than good             | Twitter              |
| 34 | 134 | ISO brings more harm than good                 | International Organization for Standardization |
| 35 | 135 | Conscientious objectors are justified          | Conscientious objector |
| 36 | 136 | The American Bar Association brings more good  | American Bar Association |
| 37 | 137 | Digital rights management brings more good     | Digital rights management |
| 38 | 138 | We should ban the Church of Scientology       | Church of Scientology |
| 39 | 139 | eBay brings more good than harm                | eBay                 |
| 40 | 140 | We should abolish the caste system in India    | Caste system in India |
| 41 | 141 | We should abolish infant baptism               | Infant baptism       |
| 42 | 142 | EHRs bring more harm than good                 | Electronic health record |
| 43 | 143 | Wildlife management brings more good than harm | Wildlife management  |
| 44 | 144 | We should tax plastic bags                    | Plastic bag          |
| 45 | 145 | The energy industry should be nationalized     | Energy industry      |
| 46 | 146 | We should fight protectionism                  | Protectionism        |
| 47 | 147 | We should limit genetic testing                | Genetic testing      |
| 48 | 148 | We should end manned spaceflights              | Human spaceflight    |
| 49 | 149 | Extra-curricular activity should be mandatory  | Extracurricular activity |
| 50 | 150 | We should abolish homework                    | Homework             |

Table 15: Test topics
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