Exploiting Debate Portals for Semi-Supervised Argumentation Mining in User-Generated Web Discourse

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Abstract

Analyzing arguments in user-generated Web discourse has recently gained attention in argumentation mining, an evolving field of NLP. Current approaches, which employ fully-supervised machine learning, are usually domain dependent and suffer from the lack of large and diverse annotated corpora. However, annotating arguments in discourse is costly, error-prone, and highly context-dependent. We asked whether leveraging unlabeled data in a semi-supervised manner can boost the performance of argument component identification and to which extent is the approach independent of domain and register. We propose novel features that exploit clustering of unlabeled data from debate portals based on a word embeddings representation. Using these features, we significantly outperform several baselines in the cross-validation, cross-domain, and cross-register evaluation scenarios.

1 Introduction

Argumentation mining, an evolving sub-field of NLP, deals with analyzing argumentation in various genres, such as legal cases (Mochales and Moens, 2011), student essays (Stab and Gurevych, 2014a), and medical and scientific articles (Green, 2014; Teufel and Moens, 2002). Recently, the focus of argumentation mining has also shifted to the Web registers (such as comments to articles, forum posts, or blogs) which is motivated by the need of retrieving and understanding ordinary people’s arguments to various contentious topics on the large scale. Applications include passenger rights and protection (Park and Cardie, 2014), hotel reviews (Wachsmuth et al., 2014), and controversies in education (Habernal et al., 2014).

Despite the plethora of existing argumentation theories (van Eemeren et al., 2014), the prevalent view in argumentation mining treats arguments as discourse structures consisting of several argument components, such as claims and premises (Peldszus and Stede, 2013). Current approaches to automatic analysis of argumentation usually follow the fully supervised machine-learning paradigm (Biran and Rambow, 2011; Stab and Gurevych, 2014b; Park and Cardie, 2014) and rely on manually annotated datasets. Only few publicly available argumentation corpora exist, as annotations are costly, error-prone, and require skilled human annotators (Stab and Gurevych, 2014a; Habernal et al., 2014).

To overcome the limited scope and size of the existing annotated corpora, semi-supervised methods can be adopted, as they gain performance by exploiting large unlabeled datasets (Settles, 2012). However, unlike in other NLP tasks where data can be cheaply labeled using for example distant supervision, employing such methods in argumentation mining is questionable. First, argumentation is an act of persuasion (Nettel and Roque, 2011; Mercier and Sperber, 2011) but not all user-generated texts can be treated as persuasive (Park and Cardie, 2014; Habernal et al., 2014), thus the selection of an appropriate unlabeled dataset represents a problem on its own. Second, argument components (e.g., claims or premises) are highly context-dependent and cannot be easily labeled in distant data using predefined patterns. So far, semi-supervised methods for argumentation mining remain unexplored.

In this article, we tackle argumentation min-
ing of user-generated Web data by exploiting debate portals—semi-structured discussion websites where members pose contentious questions to the community and allow others to pick a side and provide their opinions and arguments in order to ‘win’ the debate.\footnote{For instance createdebate.com or debate.org} Our first research question is whether debate portals (which contain noisy user-generated data) can be utilized in a semi-supervised manner for fine-grained identification of argument components. As a second research question, we investigate to what extent our methods are domain independent and evaluate their adaptation across several domains and registers.

Our contribution is three-fold. First, to the best of our knowledge, we present the first successful attempt to semi-supervised argumentation mining in Web data based on exploiting unlabeled external resources. We leverage these resources and derive features in an unsupervised manner by projecting data from debate portals into a latent argument space using unsupervised word embeddings and clustering. Second, our novel features significantly outperform state-of-the-art features in all scenarios, namely in cross-validation, cross-domain evaluation, and cross-register evaluation. Third, to ensure full reproducibility of our experiments, we provide all data and source codes under free licenses.\footnote{https://github.com/habernal/emnlp2015}

\section{Related work}

Analysis of argumentation has been an active topic in numerous research areas, such as philosophy (van Eemeren et al., 2014), communication studies (Mercier and Sperber, 2011), and informal logic (Blair, 2004), among others. In this section, we will focus on the most related works on argumentation mining techniques in NLP in the first part, with an emphasis on Web data in the second part.

Mochales and Moens (2011) based their work on argumentation schemes (Walton et al., 2008) and experimented with Araucaria and ECHR datasets using supervised models to classify argumentative and non-argumentative sentences ($\approx 0.7 F_1$) and their structure. Feng and Hirst (2011) classified argument schemes on the Araucaria dataset, reaching 0.6-0.9 accuracy. Experiments on this dataset were also conducted by Rooney et al. (2012), who classified sentences to four categories (\textit{conclusion}, \textit{premise}, \textit{conclusion-premise}, and \textit{none}) and achieved 0.65 accuracy. These approaches assume the text is already segmented into argument components. Stab and Gurevych (2014b) examined argumentation in persuasive essays and classified argument components into four categories (\textit{premise}, \textit{claim}, \textit{major claim}, \textit{non-argumentative}) using SVM and achieved 0.73 macro $F_1$ score. They further classified argument relations (support and attack) and reached 0.72 macro $F_1$ score. The best-performing features were structural features (such as the location or length ratios), as persuasive essays usually comply with a certain structure which can be seen as a potential drawback of this approach.

Regarding user-generated Web data, Biran and Rambow (2011) used naive Bayes for classifying justification of subjective claims from blogs and Wikipedia talk pages, relying on features from RST Treebank and manually-processed n-grams. In similar Web registers, Rosenthal and McKown (2012) automatically determined whether a sentence is a \textit{claim} using logistic regression and various lexical and sentiment-related features and achieved accuracy about 0.66-0.71. Park and Cardie (2014) classified propositions in user comments into three classes (\textit{verifiable experiential}, \textit{verifiable non-experiential}, and \textit{unverifiable}) using SVM and reached 0.69 macro $F_1$ score. Goudas et al. (2014) identified \textit{premises} in Greek social media texts using BIO encoding and achieved 0.42 $F_1$ score with Conditional Random Fields. The research gaps in the above-mentioned approaches are the following. First, the argumentation models are simplified to either \textit{claims} or a few types of \textit{premises/propositions}. Second, the segmentation of discourse into argument components is ignored (except the work of Goudas et al. (2014)). Recently, Boltužić and Šnajder (2015) employed hierarchical clustering to cluster arguments in online debates using embeddings projection, but in contrast to our work they performed only intrinsic evaluation of the clusters.

Debate portals have been used in a related body of research, such as classifying support and attack between posts by Cabrio and Villata (2012), or stance detection by Hasan and Ng (2013) or Got-tipati et al. (2013). These approaches consider the complete documents (posts) but do not analyze the micro-level argumentation (e.g., \textit{claims} or \textit{premises}).
3 Data

As data for training and evaluation of our methods, we use a corpus consisting of 340 English documents (approx. 90k tokens) annotated\(^4\) with argumentation by Habernal et al. (2014). Compared to other corpora mentioned in the related work, this corpus is the largest one to date that covers different domains and spans several registers of user-generated Web content. In particular, the corpus comprises four registers (comments to articles, forum posts, blogs, and argumentative newswire articles) and covers six domains related to educational controversies (homeschooling, private vs. public schools, mainstreaming, single-sex education, prayer in schools, and redshirting).

The argumentation model used in this corpus is based on extended Toulmin’s model (Toulmin, 1958). Each document contains usually one argument, where each argument consists of several argument components. There are five different components in this model, namely, the claim (the statement about to be established in the argument which conveys author’s stance towards the topic), the premise(s) (propositions that are intended to give reasons of some kind for the claim), the backing (additional information used to back-up the argument), the rebuttal (attacks the claim), and the refutation (which attacks the rebuttal). Relations between the argument components are encoded implicitly in the function of the particular component type, for instance, premises are always attached to the claim. We made two observations in the data: the claim is often implicit (must be inferred by the reader), and some sentences have no argumentative function (thus are not labeled by any argument component).\(^5\)

\(^4\)Available at www.ukp.tu-darmstadt.de/data/argumentation-mining/
\(^5\)A publication containing a thorough analysis of the dataset is pending.
comes Claim-B). After classification, the labels are mapped back to tokens (so that, for example, Claim-B sentence label is transformed to Claim-B, Claim-I, ... token labels). However, all evaluations are performed on the token level and the performance is always measured against the original token labels. Using this approximation, we lose only about 10% of $F_1$ performance.\footnote{In only 1% of the sentences there are two or more argument components in it; we arbitrarily choose the largest one.}

4.1 Baseline features

**Lexical baseline (FS0)** We encode the presence of unigrams, bigrams, and trigrams in the sentence as ‘one-hot’ (binary) features.

**Structural and syntactic features (FS1)** Since the presence of discourse markers has been shown to be helpful in argument component analysis (e.g, “therefore” and “since” for premises or “think” and “believe” for claims), we encode the first and last three words as binary features. Furthermore, we capture the relative position of the sentence in the paragraph and the document, the number of part of speech 1-3 grams, maximum dependency tree depth, constituency tree production rules, and number of sub-clauses (Stab and Gurevych, 2014b). We used Stanford POS Tagger (Toutanova et al., 2003), Berkeley parser (Petrov et al., 2006), and Malt parser (Nivre, 2009).

**Sentiment and topic features (FS2)** We assume that claims express sentiment, thus we compute five sentiment categories (from very negative to very positive) using Stanford sentiment analyzer (Socher et al., 2013) and use these values directly as features. Furthermore, in order to help detecting off-topic and non-argument sentences, we employ topic model features. In particular, we use features taken from a vector representation of the sentence obtained by using Gibbs sampling on LDA model (Blei et al., 2003; McCallum, 2002) with topics trained on unlabeled data provided as a part of the corpus.\footnote{The number of topics was empirically set to 30, therefore for each sentence the topic distribution results into 30 real-valued features.}

**Semantic and discourse features (FS3)** Features based on semantic frames has been introduced in relevant works on stance recognition (Hasan and Ng, 2013). Our features, based on PropBank semantic role labels and obtained from NLP Semantic Role Labeler (Choi, 2012), extract various semantic information (agent, predicate + agent, predicate + agent + patient + (optional) negation, argument type + argument value) and discourse markers. Discourse relations also play an important role in argumentation analysis (Cabrio et al., 2013). We thus employ binary features (such as the presence of the sentence in a chain, the transition type, the distance to previous/next sentences in the chain, or the number of inter-sentence coreference links) obtained from Stanford Coreference Chain Resolver (Lee et al., 2013). Furthermore, we include features resulting from a PTDB-style discourse parser (Li et al., 2012), such as the type of discourse relation (explicit, implicit), the presence of discourse connectives, and attributions.

4.2 Unsupervised features

We enrich the above-mentioned features by utilizing external large unlabeled resources – debate portals. They fulfill several criteria, namely (a) they are ‘argumentative’ (meant as opposed to, for example, prose or encyclopedic genres), (b) they are comprised of user-generated content and (c) and there is at least some overlap with topics from our experimental corpus. On the other hand, they contain noisy texts of questionable quality and they do not provide any specific argumentative structure (in fact, these debates are simple discussions to a topic, where each post is only labeled with a pro or contra stance). Nevertheless, we assume that the posts from (unlabeled) debate portals contain valuable information that will help us with classifying argument components in labeled data. In order to do so, we employ clustering based on latent semantics, which we now formalize as argument space features.

We assume that phrases (sentences or documents) can be projected into a latent vector space, using, typically, a sum or a weighted average of all the word embeddings vectors in the phrase; see for example (Le and Mikolov, 2014). Neighboring vectors in the latent vector space exhibit some interesting properties, such as semantic similarity (thoroughly studied within the distributional semantics area). If the latent vector space is clustered, each n-dimensional vector gets reduced to a single cluster number; such clusters have been used directly as features in many tasks, such as NER (Turian et al., 2010), POS tagging (Owoputi...
et al., 2013), or sentiment analysis (Habernal and Brychcin, 2013).

We build upon the above-mentioned approach (described by Søgaard (2013) as ‘clusters-as-features’ semi-supervised paradigm) and extend it further. We take both sentences and posts from the unlabeled debate portals, project them into a latent space using word embeddings and cluster them. The motivation is that these clusters will contain similar phrases or (similar ‘arguments’). Centroids of these clusters would then represent a ‘prototypical argument’ (note that the centroids exist only in the latent vector space and thus do not correspond to any existing sentence or post). Then we project each sentence (classification unit) in the labeled data to the latent vector space, compute its distance vector to all the cluster centroids, and encode this distance vector directly as real-valued features. By contrast to the above-mentioned works using a single cluster label as a feature, the distance vector to cluster centroids resembles a soft labeling where each sentence belongs to several clusters with a certain ‘weight’. We also use the latent vector space representation of the sentence directly as a feature vector.

As unlabeled data, we use data from two largest debate portals. As a pre-processing step we removed all posts with less than one ‘point’ earned. The data were then indexed using the Lucene framework and the top 100 debates for each of the 6 domains were retrieved which resulted into 5,759 posts (≈ 35k sentences) in the unlabeled data in total. Our approach is formalized in the following paragraph.

Argument space features (FS4) Let \( \mathbf{e}(w) \) be the embedding vector of word \( w \) and \( \text{tfidf}(w) \) be the TD-IDF value of \( w \). Sentence \( \mathbf{s} = (w_1, \ldots, w_n) \) is then projected into the embedding space \( \mathbb{E} \) as \( \mathbf{s}_e = \sum_{i=1}^{n} \text{tfidf}(w_i) \mathbf{e}(w_i) n^{-1} \) so \( \text{dim}(\mathbf{s}_e) = \text{dim}(\mathbb{E}) \). Analogically to \( \mathbf{s} \), we project the entire post \( \mathbf{a} = (w_1, \ldots, w_m) \) to the same embedding space \( \mathbb{E} \) such that \( \mathbf{a}_e = \sum_{i=1}^{m} \text{tfidf}(w_i) \mathbf{e}(w_i) m^{-1} \).

Let \( K \) be the number of sentence clusters in \( \mathbb{E} \) and \( \mathbf{c}_k \) a centroid vector of cluster \( k \in K \). Then \( \mathbf{s}_c \) denotes the distance of sentence \( \mathbf{s}_e \) to the sentence cluster centroids such that \( \mathbf{s}_c = (\cos(s_e, c_1), \ldots, \cos(s_e, c_K)) \) where \( \text{dim}(\mathbf{s}_c) = K \) and \( \cos(\bullet, \bullet) \) denotes cosine similarity. Analogically, let \( L \) be the number of post clusters in \( \mathbb{E} \) and \( \mathbf{a}_l \) a centroid vector of cluster \( l \in L \). Then \( \mathbf{a}_l \) denotes the distance of sentence \( \mathbf{s}_e \) to the post cluster centroids such that \( \mathbf{a}_l = (\cos(s_e, \mathbf{a}_1), \ldots, \cos(s_e, \mathbf{a}_L)) \). We construct the feature vector by concatenating \( \mathbf{s}_c \), \( \mathbf{s}_e \) and \( \mathbf{a}_l \).

For word embeddings, we use pre-trained skip-gram word vectors\(^{11}\) produced by Mikolov et al. (2013) \((\text{dim}(\mathbb{E}) = 300)\). To create clusters for the argument space features, we used CLUTO software package\(^{12}\) with Repeated Bi-section clustering method (Zhao and Karypis, 2002). We clustered the data using different hyper-parameters \( K \) and \( L \) (we experimented with \( K = \{50, 100, 500, 1000\} \) and \( L = \{50, 100, 500, 1000\} \)).

5 Results

We investigate three evaluation scenarios. First, we report 10-fold cross validation over all 340 documents, where the data are randomly distributed across the folds regardless of the domain or register. In this scenario, the model can benefit from domain-dependent features for the testing data, such as lexical knowledge (FS0) or domain-relevant argument space features (FS4). Second, we evaluate the cross-domain performance; the model is always trained on five domains and tested on the sixth one. In this settings, we also remove all features that exploit distant data relevant to the test set. For instance, if the test domain is mainstreaming, we exclude all debates relevant to this domain before constructing the argument space features (FS4). This evaluates the model’s cross-domain performance without any target domain data available. Finally, we test cross-register performance in two set-ups: we train the models using comments and forum posts and test on blogs and newswire articles, and then the other way round. We divided the data into these two parts based on similar properties of blogs/articles and comments/forums, such as the length, or the distribution of argumentative and non-argumentative text.

In the evaluation, we focus on \( F_1 \) scores achieved on claims, premises, backing, and non-argumentative text (the ‘O’ class). Although the

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\(^9\)createdebate.com and convinceme.net, licensed under Creative Commons (CC-BY and CC0, resp.)

\(^{10}\)‘Points’ is the sum of up-votes/down-votes by other users to the particular post. Zero-point posts were usually noisy and spam-like.

\(^{11}\)https://code.google.com/p/word2vec/

\(^{12}\)http://www.cs.umn.edu/~karypis/cluto
classifier is trained and tested on all 11 classes including rebuttal and refutation, we do not report performance of these two argument components—the results are very poor regardless of the parameters for two reasons. First, these classes are underrepresented in the data (Rebuttal-B/I, Rebuttal-I, Refutation-B and Refutation-I are present in only about 4% of sentences). Second, the inter-annotator agreement reached on these classes were reported to be very low (Habernal et al., 2014).

Cross validation results Table 1 shows results for the cross-validation scenario. The human baseline in the first row is an average score between three original annotators of the dataset. The baseline features (FS0) perform poorly, yet they beat the random assignment and majority vote (< 0.12 $F_1$). The argument space features (FS4) increase the performance in every combination. The best results for claims are achieved when only discourse, sentiment, and argument space features are involved (FS3 and FS4), whereas premises and backing benefit from the presence of lexical, syntactic, and semantic features (the richest feature set). The overall average best results are obtained from a feature combination with higher level of abstraction, in particular without low-level lexical features from FS0.

After the cross validation experiments, we also fixed the hyperparameters (using grid search) to $K = 1000$, $L = 100$ for the cluster sizes and $t = 1$ and $e = 0$ for the hyperparameters of $\text{SVM}^{\text{Bmm}}$.

Cross-domain results For each domain, the cross-domain results are shown in Table 2. On average, the best results are about 0.10 $F_1$ points worse than in the cross-validation settings (Table 1). In all domains, the best average performance was achieved using only the argument space features (FS4); in four cases this system significantly outperforms all other systems ($p < 0.001$). Moreover, more high-level feature set combinations that also contain argument space features (such as FS2+FS3+FS4 or FS3+FS4) yield usually better results for particular argument components in contrast to features based on lexical or syntactic information (FS0 and FS1). For identifying non-argumentative texts, there is no clear winner with respect to feature set abstraction (in three domains the best results are achieved using FS4 but in other three domains the baseline FS0 performs best).

Cross-register results The argument space features (FS4) performs best in average also in the cross-register evaluation (see Table 3). In recognizing premises, better results were achieved by a system trained on blogs and articles and tested on comments and forum posts. Recognizing claims exhibits similar behavior. On the other hand, recognizing non-argumentative text performs better in the opposite direction. On average, the cross-register results are much worse than cross-validation and slightly worse than cross-domain results.

5.1 Error analysis

First, we quantitatively investigate errors in the cross-validation scenario. The confusion matrix in Table 4 shows that about 50-60% of errors for each argument component were caused by misclassifying it as non-argumentative (the ‘O’ class). The system tends to prefer the ‘O’ predictions because of the high presence of non-argumentative sentences in the corpus (about 57%). Backing is often confused with premises; in particular, Backing-B with Premise-B in 14%, Backing-I with Premise-I in 17%. These two argument components have a similar function—to support the claim—so the differences in the discourse (which are sometimes very subtle) confuse the system. Note that despite the confusion between these classes, the -I and -B tags mostly remain the same (the system correctly predicts whether the argument component begins or not).13

13To provide the complete picture, we also show the previously unreported classes (rebuttal and refutation). Rebuttal is usually misclassified as non-argumentative or premise, refutation as either non-argumentative, backing, or premise.
performing cross-domain system in detail.\textsuperscript{14} We randomly sampled 40 documents and manually compared the predicted arguments with the gold data. We found that 11 predicted documents were simply wrong or no argument components were predicted at all (e.g., document #1640, #1658, #1021, #5258). Most of these errors occur in blogs, which seem to convey rather complex argumentation structure (#1666, #1197, #4586, #5258). In 8 documents, we identified that only simple wrong or no argument components seemed to be valid to some extent, although this was our subjective judgment. For instance, in document #5258, the same proposition was incorrectly identified as a claim.

\textsuperscript{14}Available also as PDF at https://github.com/habernal/emnlp2015; we use #ID to point to the particular document.

By analyzing the predicted output, we also found that in 12 documents the recognized argument components seemed to be valid to some extent, although this was our subjective judge. For instance, in #4285 (see Figure 2), the first premise was misclassified as a claim. The gold-data argument was annotated as an enthymeme (with implicit claim that advocates private schools), while in the prediction, the same proposition was identified as the an explicit claim supporting private

Table 2: \(F_1\) results for the cross-domain evaluation scenario ranked by performance. Feature set combination naming (the FS column) is explained in Section 4.1. Class labels: B-B/I = Backing-B/I, C-B/I = Claim-B/I, O = non-argumentative, P-B/I = Premise-B/I. Diamond (\(\diamond\)) in the last (winning) row signals a significant difference between this row and all other rows while star (\(*\)) denotes that the row is significantly better than the previous row; \(p < 0.001\) using exact Liddell’s test (Liddell, 1983).

Table 3: \(F_1\) results for the cross-register evaluation scenario ranked by performance. Feature set combination naming (the FS column) is explained in Section 4.1. Class labels: B-B/I = Backing-B/I, C-B/I = Claim-B/I, O = non-argumentative, P-B/I = Premise-B/I. Diamond (\(\diamond\)) in the last (winning) row signals a significant difference between this row and all other rows; \(p < 0.001\) using exact Liddell’s test (Liddell, 1983).
schools with one premise why the education was not satisfying, which might be also another valid interpretation. The second example #2180 in Figure 2 shows that the boundaries of the predicted premises are mixed up (two recognized instead of three), but the longer backing is also meaningful. These examples demonstrate that argument analysis is in some cases ambiguous and allows for different valid interpretations.

6 Conclusion

In this article, we proposed a semi-supervised model for argumentation mining of user-generated Web content. We developed new unsupervised features for argument component identification that exploit clustering of unlabeled argumentative data from debate portals based on word embeddings representation. With the help of these features we significantly improved performance of the argumentation mining system and outperformed several baselines. While the improvement was decent in cross-validation scenario, we gained almost 100% improvement in cross-domain and cross-register settings.

We evaluated the methods on a publicly available corpus annotated with argumentation that origins from user-generated Web data. By a detailed analysis of the errors, we pointed out the strengths (such as domain adaptability) and weaknesses (such as unsatisfying results for rebuttal and refutation components), as well as the challenges for the argumentation mining task (such as boundary identification issues or ambiguous arguments). If we put our results into the context of existing works, the most relevant one by (Goudas et al., 2014) achieved 0.42 $F_1$ score on identifying only premises. We get comparable results in the cross-validation settings ($F_1$ 0.31-0.40) yet with more complex argumentation model (five different components).

Although argumentation mining in user-generated Web discourse has a long way to go (our methods currently achieve only about 50% of human performance), we see a huge potential for various future tasks, such as information seeking for better-informed personal decision making or support for argument quality assessment. To foster the research within the community, we provide all source codes and data required for the experiments under free licenses.

Acknowledgements

This work has been supported by the Volkswagen Foundation as part of the Lichtenberg-Professorship Program under grant No I/82806 and by the German Institute for Educational Research (DIPF). Access to the CERIT-SC computing and storage facilities provided under the programme Center CERIT Scientific Cloud, part of the Operational Program Research and Development for Innovations, reg. no. CZ. 1.05/3.2.00/08.0144, is greatly appreciated. Lastly, we would like to thank the anonymous reviewers for their valuable feedback.

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Gold

[premise: I sent my kid to private school so that she could get a better education.] [backing: She was at a public school that was 90% Hispanic. I found that the diversity you get in a co-ed environment was lacking. As someone who went to a same sex school for 8 years, I found it lacking the diversity you get in a co-ed environment. I also think that the opposite sex education.

Gold

[claim: Personally I’d go co-ed.]

[backing: As someone who went to a same sex school for 8 years, I found it lacked the diversity you get in a co-ed environment.]

Premise: I found the attitude and behaviour of students in the co ed school to be better, and I attribute that to the influence of the opposite sex.]

Premise: There’s no doubt boys behave a little different when girls are watching, and I also found boys were quite good at limiting the bitchyness girls are renowned for. So both kept one another in line, and made for a more positive and dynamic environment.

Premise: I also think there’s a few extra life lessons and skills children can learn at co ed schools.

Premise: Dating, relationships, interacting with the opposite sex, I think children at co ed schools tend to have a far better grasp of these skills then students who’ve only attended same sex schools.

(b) Doc #2180 (forum post, single-sex education)

Figure 2: Examples of gold data annotations (on the left-hand side) and system predictions in the best-performing cross-domain evaluation scenario (on the right-hand side).

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