Stance Classification, Outcome Prediction, and Impact Assessment: NLP Tasks for Studying Group Decision-Making

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Abstract

In group decision-making, the nuanced process of conflict and resolution that leads to consensus formation is closely tied to the quality of decisions made. Behavioral scientists rarely have rich access to process variables, though, as unstructured discussion transcripts are difficult to analyze. Here, we define ways for NLP researchers to contribute to the study of groups and teams. We introduce three tasks alongside a large new corpus of over 400,000 group debates on Wikipedia. We describe the tasks and their importance, then provide baselines showing that BERT contextualized word embeddings consistently outperform other language representations.

1 Introduction

In the study of groups and teams, measuring discussion quality - plainly, what makes a group debate good? - is an open research area. Controlled behavioral studies have shown, for instance, that creativity, diversity, and conflict have major roles to play in the quality of teamwork (Caruso and Williams Woolley, 2008). But the value of diverse discussion and open conflict is complicated, with a long history of positive, negative, and null results, depending on the narrow construct being studied (Jehn et al., 1999). What is clear is that the particulars of how teams are composed and how team-mates interact with each other matters a great deal for effective group work (Milliken et al., 2003; Kozlowski and Ilgen, 2006).

In behavioral science, questions are often explored through structured equation modeling and multivariate regressions, allowing behavior scientists sophisticated control over exogenous (fixed, external) variables, like demographics and task conditions, as well as process variables that describe observable behaviors in the groups being studied (Cheung and Lau, 2008). Reducing team dynamics from text transcripts to quantitative process variables is computationally complex; in practice, text data is often ignored in favor of proxies like count statistics or, more frequently, participant survey responses (Beal et al., 2003).

These proxies are reliable and effective as stand-ins, but put a limit on the types of questions that can be asked. Scientists studying teams may wish to evaluate which voices truly influenced a conversation, gauge the diversity of people or ideas represented in those influential roles, and measure observed conflicts and consensus-building. They may also want to assess whether any particular participant impacted the discussion and use these variables in aggregate to find which processes impact quality. This data is difficult to extract from discussion transcripts.

Of course, large-scale corpus analysis is common in natural language processing, with many efficient representations of the complex underlying meaning of texts. In this work, we use these methods in the domain of group decision-making research, with three tasks for studying groups:

- **Stance classification**, a fine-grained, fully supervised classification task for individual contributions to a discussion.
- **Outcome prediction**, a distantly supervised task requiring far less annotated training data for new domains.
- **Individual impact assessment**, an unsupervised extension of outcome prediction to quantify how individual contributions or users influenced debate.

In the rest of this work, we demonstrate that these tasks are tractable for NLP researchers to-
day, especially with modern language representations like BERT (Devlin et al., 2018). This contextual representation is highly accurate in both supervised tasks and produces interpretable results for the unsupervised task, suggesting it is ready for immediate application in social science research. Alongside these results, we also introduce a real-world corpus of over 423,000 debates from Wikipedia, preprocessed and released under an open source license.

2 Background

2.1 Prior Work on Groups

Group discussion data is commonly used in NLP research. Datasets include the multiparty in-person group work of the AMI meeting corpus (McCowan et al., 2005) and the pair task-based dialogues in the MapTask corpora (Anderson et al., 1991; Bard et al., 1996). A range of core tasks have improved based on these corpora, including diarization (Anguera et al., 2012), laughter detection (Petridis and Pantic, 2008), and summarization (Riedhammer et al., 2010). In online contexts, group debates have been analyzed for tasks like argument mining (Mao et al., 2014) and stance classification (Sobhani et al., 2015), among others.

Outside of NLP venues, though, most studies of groups and organizations do not perform sophisticated text mining or analysis. Methods vary; some research focuses on fuzzy logic or economic agent modeling (see Pérez et al. (2018) for a recent systematic review), while others focus on social factors, network analysis, and the interactive aspects of teams (see Levine et al. (1993); Hackman (2011)). Here we do not address open-ended discussions, focusing on task-based debates where multiple people participate, a fixed set of options are available, and there is no gold standard “correct” answer (in social psychology, “Decision-Making Tasks,” from McGrath (1984)).

In these tasks, dysfunction leads to poor outcomes. Low-quality group discussion can focus on already-shared knowledge, rather than new problem solving; high-performing groups by contrast have specific characteristics like shared values, mental models, and communication styles, and nuanced patterns of conflict and consensus-building (Stasser and Titus, 1985). But getting at these patterns quantitatively is complex - most social science research instead avoids the question of extracting structure directly from text, instead relying on direct observable variables and survey data (Jehn et al., 1999), or simulation with explicit preferences encoded in modeled agents (Chiclana et al., 2013). In most work on group decision-making (with the notable exception of some collaborative learning settings, see Rosé et al. (2008)), automated discourse analysis is rare.

2.2 Prior Work on Wikipedia

We situate our study in a corpus of Wikipedia data. Ours is far from the first work in this domain, with hundreds of papers published over the last two decades (Mesgari et al., 2015). Large corpora of user discussions on Wikipedia have previously been collected for NLP (Prabhakaran and Rambow, 2016; Hua et al., 2018), though most study discussion in the general case rather than in decision-making contexts. We specifically study Articles for Deletion debates (hereafter, AfD). In this setting, editors nominate pages for debate that they believe should be removed from the wiki, and other editors debate whether to keep or delete the page. Other reviews of deletion discussions were published during Wikipedia’s peak almost a decade ago (Taraborelli and Ciampaglia, 2010; Lam et al., 2010; Geiger and Ford, 2011); since then, only a handful of studies have evaluated this domain, mostly in the context of argument structure mining (Schneider et al., 2013). Since the most recent comprehensive study of AfD (Lam et al., 2011), available data has nearly tripled.

The challenges of maintaining good discussion quality are directly applicable to Wikipedia. The health of production communities online requires good working conditions for users, who are volunteers (Halfaker et al., 2011); however, many attempts at improving experiences actually decrease productivity and retention (Schneider et al., 2014). The AfD process is not amenable to automation or algorithmic decision-making; instead, it is the process itself and the quality of interactions that must be prioritized and improved over time. Better metrics for teamwork could therefore have an immediate effect on the site’s policy and practice.

3 Context and Data

When a page is nominated to AfD, a group decision-making task begins. Any user (including unregistered users, provided they sign their
post with an IP address) can participate, providing either votes or comments. Votes are public, signed, and timestamped; they contain a labeled stance followed by a rationale for why they believe an article should be kept or removed from the wiki. Non-voting comments, either in direct reply to the nomination, a vote, or other comments, contain only rationales and not labeled preferences. The structure of these votes and comments follows the standard “reply tree” model of online forums (Aragón et al., 2017).

After nomination, discussions are held open for at least seven days. Discussions are then closed by an administrator, who determines the discussion outcome. While this is not a popular vote, administrators rarely deviate from group consensus. Administrators may also close another seven days of discussion, or close discussions with a verdict of No consensus. When that happens, articles are kept by default.

Figure 1 gives an example of how these dynamics play out in practice for the article “Missed Call.” The nominating statement cites the “Wikipedia is not a dictionary” policy and lack of sources to open the debate:

Orderinchaos (nomination): Seems to fail WP:NOT; is essentially social commentary and no references are given for the major assertions presented.

This statement is followed by votes and comments, which also contain rationale texts. User preferences for Delete and Keep are given in bold, with some users voting to remove the page, some to keep, and discussion occurring through followup comments:

Jmlk (voting for Delete): “Just a junk article, not notable.”

Ankur Jain (voting for Keep): “I added enough links to merit inclusion.”

Lenticel (voting for Keep): “this thing is very prevalent in our culture. See [1].”

Ankur Jain (comment): “just because you guys don’t know about the widespread use of this thing, that does not mean it does not exist”

After a long discussion and a total of eight votes and thirteen comments from ten total participants, the decision was made in favor of Keep.

3.1 Notation

For any discussion \( d \), we say that it has length \( N \) corresponding to the number of contributions \( c_0, c_1, \ldots, c_N \), which are nominating statements, comments, or votes. Each contribution \( c_i \) has a corresponding tuple \((u_i, t_i, r_i, l_i)\) representing extracted user, timestamp, rationale text, and stance label, respectively. In our corpus we provide two possible labeling schemes \( L \), a 2-label case for binary classification (which we use), and a 5-label case for direct comparison with prior work like Lam et al. (2010):

\[
L_2 = \{\text{Delete,Keep}\}
\]

\[
L_5 = \{\text{Delete,Keep,Merge,Redirect,Other}\}
\]

In any discussion, the initial contribution \( c_0 \) is the nominating statement, which is assumed to have a preference \( l_0 = \text{Delete} \). For comments, \( l_i = \emptyset \). Table 1 gives distributions of these labels in our corpus; the two primary labels dominate. The largest difference between vote and outcome distributions is from No consensus results, which default to Keep in practice.
Table 1: Distribution of preference labels in votes and final outcomes in our corpus.

| Label   | 5-Label | 2-Label |
|---------|---------|---------|
|         | Vote    | Final   | Vote    | Final   |
| Delete  | 54.9    | 64.0    | 62.3    | 73.0    |
| Keep    | 28.5    | 20.5    | 37.7    | 27.0    |
| Merge   | 3.6     | 3.1     |
| Redirect| 3.8     | 5.9     |
| Other   | 9.3     | 6.5     |

3.2 Corpus and Experimental Details

We evaluate an offline database of all Articles for Deletion discussions\(^4\). The snapshot contains approximately 19 million pages. Over one third of the pages in the administrative Wikipedia: namespace are archives related to AfD. We include all data from January 1, 2005 to December 31, 2018. Prior to 2005, traffic was low and decision-making dynamics were erratic, while data from 2019 is (as yet) incomplete. This 14-year window includes over 423,000 discussions.

For all machine learning results, we train a logistic regression classifier implemented in Scikit-Learn (Pedregosa et al., 2011) with L2 regularization and the LIBLINEAR solver (Fan et al., 2008). Experiments represent average results of 10-fold cross-validation. All instances from a particular discussion appear in only one fold; there is never crossover from the same debate between train and test data. We report results on a randomized subset of 5% of the corpus, approximately 20,000 discussions.

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For further details on data release and corpus preprocessing, including how free-form preference labels were collapsed, see Appendix A.

3.3 Language Representations

We consider three representations of language. First, we extract standard binary unigram bag-of-words features \(\phi_{BoW}(c)\). These were the standard representation of text data for decades and are still in widespread use (Jurafsky and Martin, 2014).

Bag-of-words models struggle in classification tasks for short texts, where sparsity is a significant problem. The most effective recent solution to this has been word embeddings, where words are represented not as a single feature but as dense vectors learned from large unsupervised corpora. This allows similar words to have approximately similar representations, and effectively manages sparsity. In our experiments we test a widely-used and effective word embedding model, GloVe (Pennington et al., 2014), set to the maximum of 300 dimensions and represented as \(\phi_{GloVe}(c)\).

The newest word embedding models are contextual. Rather than encoding a word’s semantics as a static high-dimensional vector, these models adjust the representation of words based on the words they appear near at classification time. This approach, combined with extensive pre-training, has led to improvements on numerous tasks. We use the most effective model to date, the \(BERT_{BASE}\) model from Devlin et al. (2018) with 768-dimensional embeddings \(\phi_{BERT}(c)\). This model was already trained on Wikipedia texts (and other sources), so we perform no fine-tuning\(^5\).

4 Turn-Level Stance Classification

In most other collaborative team decision-making contexts, opinions are expressed but explicit stances are latent. Because of the unique format of Wikipedia discussions, those stances are easily extracted from “‘bolded’” votes. We use this as a test case for building supervised classifiers which elicit participant stance based on their statements alone. All bolded text is masked from rationales and models must predict what vote is associated with a given rationale.

Similar tasks have been effective in labeling turns in prose text (see Wilson et al. (2005) and other work with their MPQA corpus), open-ended group dialogues (Stolcke et al., 2000; Mu et al., 2012), and in stance classification for more open-ended social media (Sobhani et al., 2015); here we apply the task to contributions in a structured group decision-making context.

Fundamentally this is a test of how closely the Wikipedia domain hews to other decision-making contexts. If rationales are not sufficient to predict

\(^4\)From the January 1, 2019 snapshot dumps.wikimedia.org/enwiki/20180701

\(^5\)This may mean text from our corpus is included in \(BERT_{BASE}\) training data, causing a minuscule exposure to test data in our experimental setup; we do not investigate this question here, but note it as a complicating factor.
Table 2: Accuracy of stance classification models for individual contributions, based on rationale text alone.

| Representation      | Accuracy % | \( \kappa \) |
|---------------------|------------|-------------|
| Majority Class      | 63.8       | 0.00        |
| GloVe               | 76.0       | 0.45        |
| Bag-of-Words        | 81.8       | 0.59        |
| BERT                | 82.0       | 0.60        |

Table 5: Discussion-Level Outcome Prediction

The prior task is a useful proof-of-concept that text rationales carry recognizable stance information and can be reliably recognized. With that being said, the task has limitations for practical use in other group decision-making research. Foremost, it requires training data with labeled votes; this is difficult to get in many cases. Moreover, the stances of individual votes in a discussion are too granular for process variables that aim to represent discussion dynamics overall.

A more relevant goal for social scientists is analysis of group discussions where the preferences of individuals are unlabeled, even in training data. Next, we aim to predict the consensus preference of a group, after discussion. This task measures whether language representations can model the many turns in a discussion and mimic the behavior of administrators. To do this, we give as input the rationale texts of nominations, votes, and comments throughout a discussion, and treat the label from administrative closure of a debate as the only supervised label of group consensus.

The prior task is a useful proof-of-concept that text rationales do carry this information, but they are not tractable with current NLP methods. To evaluate this, we define a task to label each vote in each AfD discussion:

- **Possible Labels:** \( L = \{ \text{Delete}, \text{Keep} \} \)
- **Input:** Rationale text \( r_i \) from a single vote.
- **Features:** A representation vector \( \phi(c_i) \).
- **Output:** A predicted stance \( l \in L \).

We exclude the problem of classifying stance in non-voting comments from our analysis, as no gold labels are available for supervised training. Expansion to distant supervision, where user stances from votes are used as gold labels for that user’s comments, is a possibility for future work.

4.1 Results

User stances are explicitly given by users in the original corpus and there is no ambiguity; the upper bound for this task is 100% accuracy and \( \kappa = 1.0 \). Individual votes or comments have short rationales, however, typically only a sentence or a few words. Despite this, \( n \)-gram models provide a robust baseline, and while the BERT model outperforms a unigram baseline, the difference is small. Comparing embeddings, the newer contextualized BERT model outperforms GloVe by more than 6% absolute and 10% relative. Overall, we find that this task is tractable, with good accuracy.

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- **Possible Labels:** \( L = \{ \text{Delete}, \text{Keep} \} \)
- **Input:** Discussion \( d \), with nomination \( c_0 \), followed by votes and comments \( c_1 \ldots c_N \). Each contribution \( c_i \) consists of:
  - User ID \( u_i \).
  - Timestamp \( t_i \).
  - Rationale text \( r_i \).
- **Features:** A representation vector \( \phi(d) \).
- **Output:** An outcome label \( l \in L \).

For our embedding representations, we again extract features \( \phi_{\text{GloVe}} \) and \( \phi_{\text{BERT}} \), but in this case there is a need to combine vectors from multiple contributions \( [c_0, c_1, \ldots, c_N] \) into a single vector for discussion \( d \). To do so, we encode each contribution’s rationale \( r_i \) separately (again removing all occurrences of “bolded” text to mask votes). We then average each contribution’s vector, normalized for length:

\[
\phi(d) = \frac{\sum_{i=0}^{N} \phi(c_i)}{\ln(\text{len}(r_i))}
\]

Unlike in the first task, outcome prediction is distantly supervised and the task is sometimes undecidable; as discussed previously, administrators occasionally close conversations with results of
No consensus. To evaluate an upper bound on model accuracy with masked preferences, we include a gold feature vector $\phi^*(d)$ where gold-standard user preference labels are made available for modeling. Specifically, for each possible $l \in L$, this vector includes the raw count and percent of votes that label received. While Wikipedia is not a direct democracy, administrators rarely deviate from consensus; this represents a good approximation of an upper bound on meaning representation from rationales alone.

As in the first task, we compare binary bag-of-words, GloVe, and BERT representations. We evaluate these models in two scenarios. First, we consider the case where we only predict outcomes after a full discussion has elapsed (Final). Second, we consider a just-in-time classifier that predicts the outcome separately after each contribution to the discussion (Real-Time). While training data includes only final discussions, $N$ separate instances are generated for testing. As such, long discussions have more influence on reported accuracy. By extension, discussions resulting in Keep are also over-weighted, as they tend to have more contributions.

5.1 Results

Table 3 shows our comparison of models. As expected, the model given access to stances of group members is highly accurate. That model is able to predict outcomes with a Cohen’s $\kappa = 0.84$ for full discussions. The BERT model also reaches good levels of agreement, outperforming other language representations by at least 1.6% absolute. In the real-time evaluation, GloVe and bag-of-words models are more competitive, but BERT maintains the highest accuracy. All models (including the gold-standard) see significant performance degradation, suggesting that discussions are not foregone conclusions after early contributions. To demonstrate this more clearly, see Figure 2, where in conversations of any length, outcome prediction early in the debate is less reliable, then improves in accuracy steadily over time as more contributions are made visible to the classifier.

6 Assessing Individual Impact

The prior two tasks were important for understanding how participants use language, and whether preferences of an individual or group are revealed through rationale texts in a discussion. Next, we aim to provide more direct value to behavioral science research, by constructing a metric $\text{Impact}(u)$ to identify the primary sources of influence in these discussions.

Our definition of impact hinges on the idea that influential contributions immediately change the likely outcome of a debate. As the basis for this measurement we follow Chouldechova (2017). That work defined “disparate impact” as the difference in expected outcomes, given circumstances that differed by exactly one variable. We borrow this definition, and evaluate impact by varying only time; specifically, we measure the expected outcome of a discussion immediately before and after each contribution is posted. To do so, we use the trained model from our outcome prediction task, in the real-time setting. For a discussion $d$ at a timestamp $t$, this gives the expected outcome label $l$ - represented as $E(l|d, t)$, using

\[\text{Impact}(u) = \sum_{i=1}^{N} \text{Impact}(u|i) \]

For the special case of nominations ($i = 0$), for each possible $P(l)$, for $l \in L$, we instead subtract the baseline probability distribution of all outcomes $l \in L$ as measured from training data.
the model trained on BERT ($\phi_B$). Thus:

$$\Delta(l, c_i) = \mathbb{E}(l|d, t_i) - \mathbb{E}(l|d, t_{i-1})$$

Probability movement in one label shifts that label upward, and another simultaneously downward, doubling the cumulative impact of changes; therefore, we sum the change in expected outcomes of all labels and introduce a normalizing factor of $\frac{1}{2}$ to produce an impact value for each contribution ranging from $[0,1]$.

$$Impact(c_i) = \frac{1}{2} \sum_{l \in L} |\Delta(l, c_i)|$$

Finally, we define impact for a user in a conversation as the sum of impacts of their contributions.

$$Impact(u) = \sum_{i=0}^{N} \begin{cases} Impact(c_i) & u_i = u \\ 0 & \text{otherwise} \end{cases}$$

This measurement of impact, based on probabilities learned from outcome prediction, again does not require any explicit labeling on the level of individuals or turns.

6.1 Evaluation

The prior two tasks were supervised, with labeled outcomes that could be measured for performance accuracy. Impact assessment has no specific ground truth to compare against. In this scenario, other NLP research has provided justifications for a mix of quantitative and qualitative evaluations, as well as validation with human annotators and evaluation based on performance improvement in downstream tasks (Louis and Nenkova, 2013; Yang, 2019). We present a mix of qualitative analysis and downstream tasks, while leaving room for future validation studies.

6.1.1 Application: Measuring Volatility

Wikipedia’s cultural preference is for open debate and a willingness to voice contrasting views (discussions should be “not a mere formality, but an integral part of writing the encyclopedia”)7. Using raw activity counts cannot measure this, partially because many contributors join late in discussions, mostly to voice agreement for foregone conclusion outcomes, a result of social rewards for editors who participate in more discussions and increase edit counts (Derthick et al., 2011).

To avoid reliance on counts, we define the volatility of a full discussion as the total amount of impact in that discussion, over all contributions:

$$Volatility(d) = \sum_{i=0}^{N} Impact(c_i)$$

We find that our this measure is effective in capturing highly contentious debates. As an illustration, the most volatile debate in our corpus was on the article8, “Justin Bieber on Twitter”. This debate which resulted in nearly 100 votes and many more comments, an article rewrite, a followup deletion review (an appeals process meant to serve an oversight function for AfD), an extended external debate on Wikipedia’s general purpose discussion board, and the establishment of prevailing policy thereafter for “[X] on Twitter” articles.

Other long debates with similarly large numbers of participants were given low volatility scores based on our outcome prediction metric. Upon inspection, these debates end with a string of repetitive votes, like “Delete. As per nom.” or “Delete. As above.” While these debates have high counting statistics, each late vote alters the expected outcome probabilities by well under 0.1%, and sometimes by less than $1 \times 10^{-5}\%.$ This is an intuitive result, accurately reproducing the qualitative findings on behaviors from Derthick et al. (2011). Additionally, this means that more “talkative” users with many contributions do not necessarily make a greater impact, even though Impact is a running sum rather than normalized by contribution count.

6.1.2 Application: Long-term Roles

We can also use outcome prediction to measure the role specific users play over time. By summing influence across all discussions, we find users who have had a disproportionate impact on the AfD process over Wikipedia’s lifespan. Ranked highly, we find users like TenPoundHammer - a user influential enough to spawn an eponymous and well-cited policy essay9, “TenPoundHammer’s Law.” The most impactful posts typically occur early in debates and are closely tied to policy (linked in double square brackets) and the broader context of Wikipedia’s social norms.

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7en.wikipedia.org/wiki/Wikipedia:Dispute_resolution
8bit.ly/2FcSNY7
9en.wikipedia.org/wiki/Wikipedia:TenPoundHammer%27s_Law
We can also evaluate average impact rather than cumulative. Here, we find users who are highly active and attentive to new debates, participating early in discussions. Our definition does not encode time explicitly, but in practice early contributions have a larger impact. This is particularly true for Keep votes to open debate, which are uniquely influential. Posting in favor of Keep immediately after a nomination influences probabilities by nearly three times as much as early Delete votes, and more than five times as much as votes that are the tenth or later contribution to a debate.

We can also find prolific users whose roles nonetheless do not had an impact on decision-making. User Captain Raju, for instance, is a highly active user primarily participating in administrative tasks like vandalism prevention and sorting, rather than voting. Despite frequent activity, their posts have an Impact measure of less than 2% on average. This matches the past finding of “mopping up” roles, which have high importance for the site and highly active users despite relatively low prestige (Burke and Kraut, 2008; Yang et al., 2017). The BERT-powered metric may therefore be useful for role identification.

Overall, our findings show that our Impact(u) rating matches intuitions when given concrete examples, and is able to give interesting insights into group decision-making dynamics longitudinally and in specific circumstances.

7 Discussion

7.1 Opportunities for NLP

Our error analysis shows that on top of support for social sciences, the remaining errors in classification will only be resolved with improved NLP methods. For instance, in stance classification, there are some cases where individual contributions simply lack the content that is necessary to classify them accurately (e.g. “Per all the above.”). These cases would benefit from a more detailed awareness of threads of conversation (Zhang et al., 2018). Even more often, classification errors occur when users themselves express uncertainty:

Instances like these require not just classification for stance but also for uncertainty (Forbes-Riley and Litman, 2011). Multi-task learning is a particularly fruitful domain for neural methods and the public release of our full corpus should be a resource for development of that field.

In outcome prediction, we find that text models underperform the gold-labels model when predicting an outcome of Keep, particularly for short debates. As seen in Table 4, when predicting Delete in short discussions, the BERT model is almost always accurate; as conversations grow, Delete predictions become less reliable, at just over 75% for debates longer than 10 contributions.

By contrast, when BERT predicts Keep it becomes more accurate as conversations grow. In short discussions where the final outcome was Keep, performance is at its worst, with a gap in accuracy over 22% compared to the gold model. In conjunction with our Impact metric evaluation, this suggests that there is significant opportunity to better identify persuasive early Keep votes, which are elusive in existing representations.

Further technological advances may also focus on recognizing short discussions that ought to be enhanced with additional evidence, either through intelligent routing to potential participants or direct intervention with relevant content. When the outcome prediction expects a Keep decision and few users have participated, there is an opportunity for the gap in debate to be filled with decision support aids showcasing the potential of NLP.
7.2 Further Validation of Impact Measures

Our work evaluating impact as a metric, using downstream interpretation tasks as a measure of success, is preliminary. Prior work in the NLP community has developed evaluation metrics hand-in-hand with human input, aiming for high correlation with their judgments (cf. Papineni et al. (2002); Banerjee and Lavie (2005) in machine translation, and Lin (2004) in summarization). This is a natural next step for this work.

Once validated, impact assessment has immediate applications. Distinguishing the impact of individuals will enable deeper process analysis of the impact of diversity on teams (Bear and Williams Woolley, 2011), the interplay between individual participants and the process of resolving conflicts or disputes (Jehn et al., 1999), and the granular habits that lead to effective outcomes. These habits are often process-oriented, small-scale, and not adequately captured by survey or demographic variables (Riedl and Williams Woolley, 2017), opening exciting new dimensions for behavioral science research.

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A Appendix

A.1 Corpus Preprocessing

Compared to the broader internet, Wikipedia is simpler to preprocess due to the rigid formality of the archival process, the MediaWiki markup language, and enforced community standards. For most tasks, we are able to extract names, timestamps, and labels with only regular expressions.

Extracting Timestamps

AfD discussion norms require that all contributions are signed using a standard format, which includes the contributor’s username or IP address and a timestamp in UTC format\(^\text{10}\). All lines following the outcome are checked for timestamps in Wikipedia standard format\(^\text{11}\):

\[
\d\d:\d\d, \w+ \d+, 20\d\d\d \text{ (UTC)}
\]

Extracting outcomes

AfD discussions are archived in a specific format with only minor variation, and can be easily extracted for structured representation. We define a discussion as having an outcome if its archival page includes a header line with one of three fixed phrases (ignoring whitespace):

- The result of the debate was [x]
- The result was [x]
- The result of this discussion was [x]

We save the captured string [x] as the debate outcome. When these lines are timestamped, we also log the user and timestamp of the outcome.

Extracting nominations, votes, and comments.

If a timestamped contribution appears at the top of the discussion, prior to any votes, it is treated as a nomination. These statements have become more common over time: while they occur in only 67% of nominations in 2005, they were rapidly adopted and are present in 98% of nominations since 2008\(^\text{12}\).

Following the nominating statement, any timestamped line is captured as either a vote or a comment. We define votes as any timestamped line beginning with a bolded phrase, following Wikipedia convention for contributions:

```
* ''\[y]''
```

Posts beginning with one or more leading asterisks creates a bulleted, threaded discussion. Words or phrases surrounded with three apostrophes creates """"bolded"""" text. The value of this bolded text \[y] is captured and stored. If no bolded phrase is present, but the line is still signed and timestamped, that line is treated as a comment\(^\text{13}\). Lines with no timestamped signature are discarded.

Several alternative solutions to deletion exist; each maintains the content of the page while deleting the page itself. In the five-label case, Merge and Redirect, the two most common alternate outcomes, are represented separately in line with prior work; in the two-label case they are merged in with Delete. All other values are grouped together as Other in the five-label case\(^\text{14}\); in the two-label case they are merged in with Keep. Votes and outcomes of “Close”, “Withdraw”, and “Cancel” are treated as “Keep” outcomes as the page as well as its content is fully maintained. Copyright violations are treated as a “Delete” outcome, as the content is deleted as a result of the outcome. Any given vote or outcome is represented as a set that can contain zero or more normalized labels. Therefore, the probability of a vote for a particular label is not drawn from a distribution; probabilities of each label in \(L\) are disjoint.

Extracting users

For each nomination, outcome, vote, or comment, we log the user whose signature immediately appears before the timestamp, either with a Mediawiki link to their User page or their User Talk page:

```
[[User Talk:z]]
[[User:z]]
```

We extract \[z\] as a username and associate it with the nomination, outcome, vote, or comment where it was captured. When user signatures link to both User and User Talk pages and those usernames differ, the Talk page’s username is prioritized.

---

\(^\text{10}\)These signatures are highly formulaic and easy to extract, because they can be automatically generated by MediaWiki’s `\[\]` shorthand. When users do not sign contributions, bots add them, along with a citation to the SIGNATURES policy.

\(^\text{11}\)In regular expressions, \w matches any letter and \d can match any numeric character. A + suffix captures one or more consecutive characters of that type.

\(^\text{12}\)Under present policy, omitting a nominating statement is an acceptable reason for “speedy” dismissal and default “Keep” outcome for an AfD nomination.

\(^\text{13}\)Lines beginning with the bolded phrase “Comment” are also treated as comments. Lines beginning with “Note” are automatically generated, typically for categorizing discussions by topic, and are discarded. Lines with “Relist” bolded are administrative notes to keep the discussion open for longer than the typical seven days, and are also discarded.

\(^\text{14}\)“Userfy”, “Transwiki”, “Move”, and “Incubate”
A.2 Reproducibility

The public release of this corpus will include designated fold assignments for reproducible results and future comparisons against baselines on the 5% subset used in this work. We will also include two formats for experimenting with the full corpus: a 10-fold cross-validation split, as well as a single train/validation/test split for use with more resource-intensive classifiers, especially neural methods.

The library that we developed for producing these variables is written in Python and compatible with standard implementation of BERT and a standard JSON format for representing group discussions.