In Opinion Holders’ Shoes: Modeling Cumulative Influence for View Change in Online Argumentation

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ABSTRACT

Understanding how people change their views during multiparty argumentative discussions is important in applications that involve human communication, e.g., in social media and education. Existing research focuses on lexical features of individual comments, dynamics of discussions, or the personalities of participants but deemphasizes the cumulative influence of the interplay of comments by different participants on a participant’s mindset. We address the task of predicting the points where a user’s view changes given an entire discussion, thereby tackling the confusion due to multiple plausible alternatives when considering the entirety of a discussion.

We make the following contributions. (1) Through a human study, we show that modeling a user’s perception of comments is crucial in predicting persuasiveness. (2) We present a sequential model for cumulative influence that captures the interplay between comments as both local and nonlocal dependencies, and demonstrate its capability of selecting the most effective information for changing views. (3) We identify contextual and interactive features and propose sequence structures to incorporate these features. Our empirical evaluation using a Reddit Change My View dataset shows that contextual and interactive features are valuable in predicting view changes, and a sequential model notably outperforms the nonsequential baseline models.

CCS CONCEPTS
- Computing methodologies → Natural language processing;  
- Theory of computation → Structured prediction;  
- Human-centered computing → Social network analysis.

KEYWORDS
Online discussion modeling, Persuasion, Social media

ACM Reference Format:

1 INTRODUCTION

Argumentative discussions are common in daily life and on social media. In settings of interest here, the participants engage in an argumentative discussion seeking to persuade each other [2]. Understanding how people change their views is valuable in applications of social media analytics that involve modeling opinions and influence, such as in political debates, product evaluations, and diffusion of new ideas. Not surprisingly, online argumentative discussions are garnering increasing research attention [12, 19, 29].

Argumentative discussions on social media, such as Twitter, Reddit, and Quora, not only provide the basis for understanding people’s thoughts and behaviors, but also enable the possibility of developing a customized information recommendation system [37, 38]. A fundamental concern for both participants and those who view or analyze discussions (e.g., for advertising or digital governance) is to deal with information overload in using knowledge from the web. Dealing with information overload requires a method that can effectively retrieve relevant information and plausible answers from massive online information.

Idiosyncrasies of individual users under varying circumstances are a source of complexity. Despite increasing attention on argumentation in social media, how and when view changes happen during an exchange of comments lacks investigation. Previous works about persuasiveness focus on statistics such as length or branching factors of the discussions, linguistic features of individual comments, and topic similarity between paired comments. In contrast, we posit that it is necessary to examine a discussion as a whole to capture the interplay of the exchanges between participants and their cumulative effect on the mental state of a participant.

We investigate how to use the most of the information in an online argumentative discussion from these two aspects. Table 1 gives a motivating example drawn from Reddit’s Change My View forum (with names changed) involving one opinion holder (Alice) and multiple challengers who hold the opposite view (Bob, Chris, Dave, and Ella).

Table 1’s scenario is a discussion initiated by Alice about the game mechanic of having random encounters in a game. Challengers raise three points in opposition: (1) old games use random encounters, (2) users prefer random encounters, and (3) random encounters are addictive. However, the second point (pt 2.0) raised by Bob is ignored by Alice at first. Chris and Dave argue with Alice on the third point, which though not explicitly related to (pt 2.0) builds up an effect on Alice about how random encounters make the game addictive and fun. And, when Ella observes in (pt 2.1) that some people love the game mechanic, Alice changes her view stating “I suddenly got sentimental about the idea.” Thus, (pt 2.0) and (pt 2.1) raise the same point but receive different credit, indicating that what matters is not the effect of one individual comment, but the cumulative influence building up unconsciously via a series of comments—(pt 2.0), (pt 3.0), and (pt 3.2) leading to (pt 2.1).

Such scenarios motivate us to focus on cumulative influence. We approach the problem of predicting when in a discussion an opinion...
Table 1: A snippet of an online argumentative discussion. OH is an opinion holder and C is a challenger. Index indicates the threading structure (e.g., comment 1.1 is a child of comment 1). Three styles of underlining delineate three opposing points.

<table>
<thead>
<tr>
<th>Index</th>
<th>Person</th>
<th>Role</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Alice</td>
<td>OH</td>
<td>Random encounters, like in the Final Fantasy series, are a bad game mechanic.</td>
</tr>
<tr>
<td>1.1</td>
<td>Bob</td>
<td>C</td>
<td>I’d argue that it’s not bad per-se, but just outdated and has no place in current games. (prt 1.0) The only reason it exists is because old gaming systems couldn’t handle anything else at the time, but (prt 2.0) it persisted through generations because people liked it.</td>
</tr>
<tr>
<td>1.1.1</td>
<td>Alice</td>
<td>OH</td>
<td>The part about old gaming systems not being able to handle anything else isn’t true.</td>
</tr>
<tr>
<td>1.2</td>
<td>Chris</td>
<td>C</td>
<td>Random reinforcement is a well-known way to make things more addictive.</td>
</tr>
<tr>
<td>1.2.1</td>
<td>Alice</td>
<td>OH</td>
<td>Being more addictive doesn’t make it a good game mechanic.</td>
</tr>
<tr>
<td>1.2.1.1</td>
<td>Dave</td>
<td>C</td>
<td>Good or bad or fun is subjective with regards to games.</td>
</tr>
<tr>
<td>1.3</td>
<td>Ella</td>
<td>C</td>
<td>A number of people who like gambling note that they enjoy that sort of mechanic.</td>
</tr>
<tr>
<td>1.3.1</td>
<td>Alice</td>
<td>OH</td>
<td>I suddenly got sentimental about the idea of random encounters and not quite wanting them to go away.</td>
</tr>
</tbody>
</table>

We consider two datasets: threaded discussions on Reddit Change My View (CMV) subreddit, and from human studies.

2 DATASETS

We consider two datasets: threaded discussions on Reddit Change My View (CMV) subreddit, and from human studies.

2.1 Reddit Change My View (CMV) data

On Reddit’s CMV forum, opinion holders award a delta (which we write as Δ, for readability) to the comments that changed their view to some extent. Each discussion is terminated after three hours. We categorize CMV posts into three types, based on where they fit in a discussion and examine them to motivate our features:

- Original post (OP)—the opening by an opinion holder (OH), which provides the initial prompt including a justification of the view in a minimum of 500 characters.
- Comment from a challenger—a reply to the OP or any subsequent comments. Typically, challengers refer to previous posts to provide counter-arguments. Agreement with the OP is prohibited in replies by CMV rules.
- Reply from the OH—to a comment from a challenger. The OHs may award Δs to challengers who caused changes to their views. We use Δs as our ground truth. However, there is no way to quantify the degree of the view change or force a Δ award by the platform.

We use the dataset provided by Tan et al. [34]. The raw dataset contains all discussions from January 2013 till August 2015, including both textual content and information such as user names, user scores, and timestamps. We filter discussions using criteria similar to Tan et al.’s. First, the fact that opinion holders enter the discussion asking for their views to be changed does not always indicate an open mind—only fewer than half of the discussions resulted in a Δ being awarded, and only a small portion of the comments (~2%) wins a Δ. Second, we exclude discussions where the OP never replied, no Δ was awarded by the OP, or there were fewer than 10 replies. Table 2 shows the statistics of our dataset.

Table 2: Statistics of the CMV dataset. Here, cmt. and dis. stand for comments and discussions, respectively.

<table>
<thead>
<tr>
<th>Count</th>
<th>cmt.</th>
<th>cmt. w/ Δ</th>
<th>dis.</th>
<th>words per cmt.</th>
<th>sentences per cmt.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Training</td>
<td>447,788</td>
<td>7,620</td>
<td>5,000</td>
<td>96.9</td>
<td>5.3</td>
</tr>
<tr>
<td>Testing</td>
<td>59,161</td>
<td>1,157</td>
<td>683</td>
<td>96.7</td>
<td>5.2</td>
</tr>
</tbody>
</table>

Our observation corroborates previous work [34] that it is difficult to identify comments that earned Δs due to the idiosyncratic ratings by opinion holders in CMV. Therefore, we conduct empirical user studies to, first, establish the validity of the data in terms of the
reliability of assignments of labels and, second, better understand the nuances of persuasive comments given their contextual and interactive features.

One note is that both Reddit CMV and the human study are settings with skewed demographically. However, this is the nature of many settings. For example, tweets about different topics attract different demographic bases. Although the feature set for this specific task may not be suitable in a different setting (i.e., features may have different weights or need to be extended leveraging domain-related factors), the results from the human study demonstrate that we need to put the model in the opinion holder’s shoes to understand why a specific opinion holder’s view would change or not change.

2.2 A Human Study

Due to the aforementioned fact that only a few of the comments win a Δ from an opinion holder, we conduct a human study on top of the CMV dataset in which participants estimate the soundness and persuasiveness of an argument. Our motivation is to provide additional finer-grained data to help us better understand the characteristics of online argumentative discussions.

We conducted the experiment with US military reservists as annotators. This study was approved by the Institutional Review Board (IRB) of our university and by the US Department of Defense. Informed consent was obtained from each participant. Considering task duration and expected qualities, we selected discussions with around 50 comments and randomly distributed them to annotators. Annotators were presented with comments from both opinion holders and challengers from a discussion and are requested to rate each comment as to its persuasiveness on a 1–5 scale, from weakly to strongly persuasive. Depending on time availability, each annotator rated one or more discussion threads.

We collected annotations of 72 discussions from 29 annotators. Table 3 shows the statistics of this dataset. Since we have a varying number of annotators for each thread, we calculated the inter-rater reliability using Krippendorff’s alpha, obtaining 0.400, which indicates fair but not high reliability. The result suggests that judgments of persuasiveness are quite subjective. It is notable that the difference of average ratings between comments with Δ and comments without Δ is slight, whereas the differences of standard deviation and variance between Δ and non-Δ comments were substantial. This observation indicates that annotators, as observers rather than participants (opinion holders), have the similar perception of persuasiveness of successful comments. The human study indicates that persuasive comments share certain traits, as discussed in previous studies [10, 35]. However, the large variance of ratings of comments without Δ indicates that perception of persuasiveness varies with each individual. To retrieve a comment that is both persuasive and effective for a certain opinion holder, we need to consider factors related to an opinion holder’s perception. We present further analysis and additional discussions on the human study data in Section 5.1.

With this human study, we enrich CMV data by annotating persuasiveness ratings on a scale at the comment level and from multiple annotators. This provides additional information for understanding individual perception of persuasiveness and modeling how people change their views.

| Table 3: Statistics of the human annotated data. Here, r denotes ratings, avg, std, and var stand for average, standard deviation, and variance, respectively. |
|-----------------|-------|--------|--------|
| Comments | count | avg(r) | std(r) | var(r) |
| Without Δ | 2844 | 3.177 | 1.042 | 1.567 |
| With Δ | 102 | 3.419 | 0.703 | 0.631 |

3 APPROACH

We formalize our problem as a sequence labeling task. Each discussion in CMV is represented as a sequence of comments sorted in increasing order of time. Our objective is to predict whether a comment in the sequence wins a Δ. Our model’s input is a sequence of comments \( x = (x_1, \ldots, x_n) \), each with a set of feature values. The model’s output is a sequence of binary labels \( y = (y_1, \ldots, y_n) \) for each comment in \( x \). A positive label (i.e., 1) means the comment changes the view of the opinion holder and wins a Δ; a negative label (i.e., 0) means it does not.

An overview of the proposed supervised sequential model (CRF) is shown in Figure 1. Discussions are encoded offline using identified features as discussed in Section 3.1. We discuss how to use CRF to represent cumulative influence and how to generate sequences from threaded discussions in Section 3.2 and Section 3.3.

3.1 Features and Revealed Traits

We coarsely categorize features influencing view change as linguistic, contextual, and interactive. This categorization is extensible since each category represent a meaningful aspect: linguistic features represent characteristics of individual comments and can be extracted purely from texts, contextual features are metadata (dynamics) of a discussion as are provided by the platform API or can be obtained by calculating statistics, and interactive features represent the pairwise relations between comments.

Our selected feature set reflects the traits of CMV comments in terms of the usage of a language, the position of a comment in the context of a discussion, and the interplay of comments.

We describe the methods for computing and quantifying features in detail in Section 4.2. We don’t seek to explore an exhaustive list of features but to demonstrate features that work well for predicting persuasiveness. However, our model is general enough to incorporate additional features that may be available for specific problems. The linguistic and contextual features are selected from the relevant literature in psychology and communication theory. Our key novelty lies in representing interactive features in a sequential model.

Linguistic features reflect persuasion strategies adopted by challengers. We employ linguistic features that are known to correlate with topics [11], argumentation, personality, and persuasion success. Linguistic features are extracted from the text of each comment with a lexicon-based approach.

Definite and indefinite articles often express specificity and generality, respectively. We might expect that people would prefer more specific over less specific information.

First-person and second-person pronouns are indicators in aspects such as openness, deception, and persuasiveness [9, 25, 28].
A first-person pronoun indicates individual experience, personal judgment, or affirmation of the information conveyed. *Hedge words* indicate uncertainty, which can indicate a weak statement or rationality and prudence. In addition, hedging is associated with indirectness in politeness theory [4], which may have an effect on an opinion holder’s mental state.

*Sentiment* strongly indicates subjectivity by conveying the polarity of an opinion. It proves effective in social network link prediction [39] and precision advertising.

*Biased language* may indicate a weakness of one’s argument. We employ linguistic cues of two major classes of bias—framing (subjectivity) and epistemological (believability of a proposition) [31].

*Other features* include examples, questions, and links, which prior work ranks as important to persuasion [29, 34].

*Contextual features* include those pertaining to discussions at large as well as to users. Contextual features reflect the dynamics of a discussion and the situation of a certain comment. Contextual features are extracted based on properties of the discussion. CMV provides information such as timestamps of posts and user’s contribution scores.

*Length of discussion* indicates the OH being entrenched and the topic being controversial.

*Entry order of a comment* is an indicator of cumulative influence up to that comment. A challenger entering late in a discussion may absorb previous information and gain a better understanding of the opinion holder’s reasoning before commenting. However, previous studies [34, 38] show that an earlier comment is more likely to earn a Δ than a later comment, possibly due to a first-mover advantage.

*Authorship* identifies OH and challengers. It reflects which parties the interplay is between.

*User’s karma score and historical Δs* indicate a user’s past engagement, especially historical discussions and contributions. Karma is calculated as the number of upvotes minus the number of downvotes earned by the user.

**Interactive features** capture explicit interaction (replies to and quotations from comments) as well as implicit interaction (relationships such as discourse structure and persuasion strategy). We examine implicit interactions at a coarse level that capture the existence of potential connections of two comments but not the type of a certain connection.

*Direct response to a comment* indicates turn taking by the OH and the challengers, sometimes ending with a Δ being awarded. Direct responses indicate coherence of two comments.

*Quotation* reflects that the points made in a comment repeat what was presented before but presumably with additional evidence or reasoning.

*Connection with OP* indicates an understanding of OH’s reasoning in the original post. Such connections appear as discussion and persuasion strategy. We examine the existence of potential connections of two comments but not the type of a certain connection.

*Response from OH* reflects an OH’s opinion on a counter-argument. For example, an OH who has strongly resisted a point in a counter-argument may not be persuaded by the same point again. Therefore, we identify dependencies between two comments and use the OH’s sentiment to the previous comment as a feature to predict the label of the later comment.

### 3.2 Sequential Model

We adopt Conditional Random Fields (CRF) [20] to capture both adjacent and nonlocal dependencies between comments.

Given a sequence of vectorized comments $x$, our model predicts a sequence of corresponding labels $y$ for each comment in $x$ using the conditional probability $P(y|x)$. In general, vertices $V$ of a CRF graph $G$ are partitioned into cliques $V_G = \{ C_1, \ldots, C_p \}$. Given a set of features, $\theta$ represents parameters of a CRF model to be estimated.
\(P(y|x)\) with parameters \(\theta\) is written as in Equation 1.

\[
P_\theta(y|x) = \frac{1}{Z(x)} \prod_{C \in V} \prod_{\epsilon \in C} \Psi_\epsilon(x, y) \tag{1}
\]

Here, each edge factor \(\Psi_{\epsilon}\) represents an edge in a clique \(c\) as shown in Equation 2: \(Z(x)\) is a normalization factor; \(f_\epsilon\) is a feature function; \(\lambda_\epsilon\) represents the weight for each feature. Parameters \(\theta = \{\lambda_\epsilon\}\) are estimated to maximize log-likelihood during the training phase.

\[
\Psi(x, y) = \exp \sum_k \lambda_k f_k(x, y) \tag{2}
\]

**Linear CRF.** When the graph structure is a sequence, the conditional probability follows the Markov assumption and considers only \(\Psi(y_t, y_{t-1}, x)\). Linear CRF is the common type of CRF in NLP, such as for POS tagging, sentence segmentation [40], and sentiment flow modeling [22].

**Skip-Chain CRF.** Skip-chain CRF uses a general CRF graph representation with higher-order dependencies. In a skip-chain CRF model, nonadjacent but dependent nodes are linked by a skip edge and such long-distance dependencies are included in the conditional distribution. Specifically, skip-chain CRFs capture nonlocal dependencies between pairs of nodes. The skip-chain CRF combines two kinds of dependencies: (1) first-order of the form \(\Psi(y_t, y_{t-1}, x)\) with first-order feature functions \(\{f_1, \ldots, f_K\}\), as in linear CRF (Equation 3 and edges in solid lines in Figure 1) and (2) higher-order of the form \(\Phi(y_u, y_v, x)\) with higher-order feature functions \(\{f_{K+1}, \ldots, f_J\}\) where \(|u - v| > 1\) (Equation 4 and edges in dotted lines in Figure 1).

\[
\Psi(y_t, y_{t-1}, x) = \exp \sum_{k=1}^K \lambda_k f_k(y_t, y_{t-1}, x) \tag{3}
\]

\[
\Phi(y_u, y_v, x) = \exp \sum_{k=K+1}^J \lambda_k f_k(y_u, y_v, x) \tag{4}
\]

### 3.3 Sequence Structures

A challenge in modeling discussions with CRF is to capture dependencies (i.e., skip edges) and context (i.e., edge factors) properly.

**Capture nonlocal dependencies and context.** As Table 1 illustrates, we identify a pair of dependent nonadjacent comments based on the interactive features. We construct a skip edge between two comments if (1) one comment is the child of the other or (2) the textual similarity between the two comments is above a certain threshold. We term these criteria Skip-Rules. Algorithm 1 describes how to form a sequence and skip edges for CRF with Skip-Rules.

**Form subsequences.** Another consideration is the size of the discussions. In our dataset, the longest discussion contains 1,980 comments and 88 branches. With additional edges representing dependencies for content-based similarities, the number of nodes in the maximum clique of the graph is large and inference can be quite inefficient. Therefore, we break a discussion down into subsequences bounded by the opinion holder’s participation (i.e., a reply from the opinion holder to previous comments).

#### Algorithm 1: Form sequences and skip-edges with dependencies and context.

**Input:** A sequence of comments sorted by time

\[x = (x_1, x_2, \ldots, x_n)\]

**Output:** A sequence of comments encoded in feature space, a list \(E\) of node pairs that are linked by skip edges

1. Extract \(R\) a set of comments that are replied to by \(OH\)
2. for each \(x_u\) in \(x\) do
   - Extract linguistic and contextual features for \(x_u\)
   - for each \(x_v\) in \(x\) where \(v < u\) do
     - if \((x_u, x_v)\) satisfies a member of Skip-Rules then
       - Add \((x_u, x_v)\) to \(E\)
       - if \(x_v \in R\) then
         - \(f(y_u, y_v)\) = sentiment score of \(OH\’s\) response to \(x_v\)
   - end
   - end
- end

Subsequences structured as explained above respect turn-taking and model a discussion of multiple rounds. Each round is represented as a subsequence. It starts with a statement or reply by the \(OH\) followed by comments from challengers who take in the latest information present in the \(OH\’s\) replies.

The \(OH\’s\) mental state may change in each round based on information received from challengers. We assume the \(OH\’s\) mindset remains unchanged within a round but potentially changes across rounds and is reflected in the \(OH\’s\) reply at the beginning of each round. Accordingly, we construct each round as a subsequence.

### 4 EXPERIMENTS AND ANALYSIS

We describe the computational methods and configurations for the experiments in detail in this section. Our code and data are released at https://github.com/zguo8/cmv-cumulative-influence.

#### 4.1 Data Preprocessing

As a prelude to building the feature space and forming skip edges, we preprocess the data to better represent specific features. From the original dataset [34], we filter out discussions (1) in which an opinion holder never replied or awarded a \(\Lambda\) and (2) that have fewer than 10 comments. We also exclude the “initiating” period of CMV (before May 2013), which shows a different level of counts of replies and counts of participants from the later period.

We remove non-ASCII characters, fill periods in place of line breaks if punctuation is missing, and exclude system messages such as deleted message marks.

#### 4.2 Feature Extraction

Table 4 describes the methods used for quantifying the features and the lexicons used in the computation.

For measuring text similarity between comments, we tokenize a pair of dependent nonadjacent comments based on A challenge in modeling discussions with CRF is to capture dependencies for content-based similarities, the number of nodes in the maximum clique of the graph is large and inference can be quite inefficient. Therefore, we break a discussion down into subsequences bounded by the opinion holder’s participation (i.e., a reply from the opinion holder to previous comments).
Table 4: List of features and explanations. Here, \( \text{len}(d) \) denotes the length of a discussion, \( \text{len}(c) \) denotes the length of a comment, and \( \text{len}(\text{subseq}) \) denotes the length of a subsequence measured by the count of comments in the subsequence.

<table>
<thead>
<tr>
<th>Categories</th>
<th>Features</th>
<th>Explanation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linguistic</td>
<td>Definite/indefinite articles</td>
<td>Occurrences normalized by ( \text{len}(c) )</td>
</tr>
<tr>
<td>Linguistic</td>
<td>1st/2nd person pronouns</td>
<td>Occurrences normalized by ( \text{len}(c) )</td>
</tr>
<tr>
<td>Linguistic</td>
<td>Hedges</td>
<td>Use the list of hedge words created by Hyland [18]</td>
</tr>
<tr>
<td>Linguistic</td>
<td>Sentiment</td>
<td>VADER compound scores [17]</td>
</tr>
<tr>
<td>Linguistic</td>
<td>Biased language</td>
<td>Occurrences of each subtype of biased text [31]</td>
</tr>
<tr>
<td>Linguistic</td>
<td>Examples</td>
<td>Occurrences of “for example” and alternative expressions</td>
</tr>
<tr>
<td>Linguistic</td>
<td>Questions</td>
<td>Count of question marks</td>
</tr>
<tr>
<td>Linguistic</td>
<td>Links</td>
<td>Count of “http” and “https” marks</td>
</tr>
<tr>
<td>Contextual</td>
<td>Length of a discussion</td>
<td>The count of the comments in a discussion.</td>
</tr>
<tr>
<td>Contextual</td>
<td>Entry order of a comment</td>
<td>Normalized by ( \text{len}(d) ) in settings with sequences; normalized by ( \text{len}(\text{subseq}) ) in settings with subsequences</td>
</tr>
<tr>
<td>Contextual</td>
<td>Authentication</td>
<td>A binary value where 1 denotes an opinion holder and 0 denotes a challenger</td>
</tr>
<tr>
<td>Contextual</td>
<td>User’s flair</td>
<td>A score on Reddit indicating a user’s contribution provided by the Reddit API</td>
</tr>
<tr>
<td>Interactive</td>
<td>Direct response to Quotation</td>
<td>Use the index of the precedent comment to which the current comment replies</td>
</tr>
<tr>
<td>Interactive</td>
<td>Connection with the OP</td>
<td>Measured by cosine similarity with USE (Universal Sentence Encoder) [6]</td>
</tr>
<tr>
<td>Interactive</td>
<td>Connection with OH’s most recent replies</td>
<td>Measured by cosine similarity to the latest reply of OH; Measured by cosine similarity with USE embeddings</td>
</tr>
<tr>
<td>Interactive</td>
<td>Response from OH</td>
<td>OH’s sentiment to the previous most-similar comment (measured by cosine similarity with USE embeddings)</td>
</tr>
</tbody>
</table>

4.3 Model Development and Configuration

We realize the linear CRF model using the sklearn-crfsuite implementation, which is an open-source Python wrapper for CRFsuite [26]. We inherit default settings of sklearn-crfsuite, where parameter estimation is performed by the L-BFGS algorithm with elastic net (L1 and L2) regularization. For labeling each item in a sequence, we use the list of hedge words created by Hyland [18] and calculate marginal probabilities to find the most likely class label.

To capture higher-order dependencies, we develop a model with the general graph CRF implementation with PyStruct [23]. The training data of the model contains two parts. One is the graph structure and the other is the feature space. During the training phase, we use the default structured SVM solver to estimate the margin as a convex optimization problem. When predicting the items in a new sequence, it approximates the maximum a posteriori probability (MAP) for labeling. For the skip-chain CRF, we choose linear programming as the inference algorithms to obtain marginal probabilities to plot the curves.

4.4 Metrics

Since our data are highly imbalanced, we choose the following metrics to evaluate the performance of our model. Section 5 discusses how we apply these metrics.

**AUC-ROC**: AUC (Area Under the Curve) scores of ROC (Receiver Operating Characteristic) measure the true positive rate (TPR) against the false positive rate (FPR). AUC score of ROC reflects whether a comment that received a \( \Delta \) is predicted to have a higher probability of a positive class label than a comment that did not receive a \( \Delta \). This metric is applied in predicting persuasiveness of arguments [19] and malleability of initial statements [34].

**AP**: Average Precision (AP) is calculated as the area under the Precision Recall Curve (PRC). PRC has gained attention in evaluating imbalanced data, since ROC provides a misleading interpretation and visualization of specificity (i.e., true negatives among predicted negatives) on imbalanced data [30, 32]. PRC provides an interpretation of specificity complementing AUC-ROC for evaluating the performance of CRFs on imbalanced data [3, 16].

**MRR**: Mean Reciprocal Rank (MRR) is the mean across all discussions of the reciprocals of the ranks at which the first relevant item (i.e., a \( \Delta \)-earning comment) is retrieved.

4.5 Baselines

Since our specific problem—predicting the points of view changes in the context of an overall discussion—is novel, there is no previous work we can directly compare to. For example, Tan et al. [34] tackle a binary classification task where input data are paired root replies—such corpus does not provide the feasibility to examine the cumulative influence from the interplay of other comments. Therefore, we evaluate our model from multiple angles as follows.

**Nonsequential models.** We choose LR (logistic regression) and SVM (Support Vector Machine) as our nonsequential baseline models. LR is a strong baseline, as it is employed in the aforementioned related work [19, 29, 34]. SVM is powerful for NLP tasks including determining the persuasiveness of an argument [7]. For logistic regression, we explore L1 and L2 regularization with different regularization strengths. We adopt the SVM model in scikit-learn [27],
in which the probabilities are calibrated using Platt scaling with additional cross-validation. For SVM, we explore linear and radial basis function (RBF) kernels. For both baselines, the class weights parameter is set to 1:5 respecting the imbalanced data. The chosen weight (1:5) performs best among a series of weights in increments of 5, specifically, 1:10, 1:15, 1:20. With this setup, the models set a smaller penalty for false positives than for false negatives.

Tan et al.’s interplay features. To evaluate the identified contextual and interactive features, we compare our feature set to Tan et al.’s interplay features by applying them on each model. Tan et al. [34] evaluate multiple feature categories such as the number of words, BOW, POS, interplay, and style features and find that the interplay features significantly outperform other features and are more robust when controlling for the length of comments in experiments. Therefore, we implemented Tan’s interplay features, encoding the comments use these features, and compare performance of a model with our proposed features to the same model but with Tan’s interplay features.

Comments replied by OH. Jo et al. [19] investigate interactions through a neural network by pairing each sentence in a challenger’s comment with every sentence in the OP. However, they examine only comments replied to by the OH and omitted comments that the OH intentionally or unintentionally ignored. To compare within Jo et al.’s result, for this specific evaluation, we only use comments that OH replied to as our input rather than all comments.

Human annotation. We obtained the ratings from reservists on a sample dataset of CMV discussions. These human annotators presumably hold different prior beliefs and have different judgments about persuasiveness from the opinion holders. Comparing to the models, the judgment from human annotators is subject to cognitive process, thus is not limited by identified features. Note that for the human annotation task, we select the discussions whose number of comments is around 50. Therefore, it results in a test set with a different positive rate (3%), which is higher than the whole original CMV dataset (2%). As an additional experiment, we test and report the results of our models for this specific dataset and compare with human performance in Section 5.1.

Random guessing. Tan et al. [34] conduct an experiment about malleability of original posts from opinion holders. They asked annotators to find the malleable one from a pair of original posts. Tan et al. report that human annotators performed no better than random guessing and LR performs only slightly better than random guessing on predicting malleability. Although our problem setting is different from the malleability study, the comments of CMV discussions yield the same randomness and subjectivity regarding their persuasiveness to opinion holders. Therefore, we include random guessing as one of the baselines. Random guessing has an AUC-ROC of 0.5 independent of the class distribution. However, the AP for random guessing is determined by the positive rate, which in our setting, is 0.02. MRR of random guessing for the test set is 0.11, which is calculated by

$$MRR(t) = \frac{1}{\text{len}(d(1))} \sum_{r=1}^{\text{len}(d)} \frac{\text{count}(d, r)}{r}.$$  

5 ANSWERING OUR RESEARCH QUESTIONS

We now revisit the research questions motivated in Section 1. Table 5 shows the comparative results—subsequent to hyperparameter optimization and three-fold cross-validation for each model.

RQ Feature. For LR, our feature set outperforms Tan et al.’s (2016) interplay features by an absolute increase of 9% on AUC-ROC and 11% on AP. Linear CRF with our feature set outperforms that with Tan et al.’s feature set by 8% on AUC-ROC and 4% on AP.

Table 6 shows the performance of each feature category using CRF. It indicates that contextual and interactive features improve performance, which supports our claim that considering the cumulative influence of all participants’ comments is important for predicting view changes.

<table>
<thead>
<tr>
<th>Feature Category</th>
<th>Linguistic</th>
<th>Contextual</th>
<th>Interactive</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP</td>
<td>0.13</td>
<td>0.19</td>
<td>0.17</td>
<td>0.23</td>
</tr>
<tr>
<td>AUC</td>
<td>0.73</td>
<td>0.84</td>
<td>0.81</td>
<td>0.87</td>
</tr>
</tbody>
</table>

To take a close look at the impact of each feature, we examine the feature weights in linear CRF. The coefficients of normalized feature values in linear CRF are learned using the optimization algorithm and represent the contribution of each feature to class prediction. Top-ranking features with positive and negative contributions to linear CRF are listed in Table 7.
Table 7: Top correlated features from Table 4.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Positively Correlated Coefficient</th>
<th>Negatively Correlated Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Links</td>
<td>0.117</td>
<td>relative order -0.674</td>
</tr>
<tr>
<td>2nd person pron.</td>
<td>0.008</td>
<td>Sim. w/ recent -0.064</td>
</tr>
<tr>
<td>User flair</td>
<td>0.005</td>
<td>Sim. w/ OH -0.055</td>
</tr>
<tr>
<td>Definite articles</td>
<td>0.003</td>
<td>Quotation -0.040</td>
</tr>
<tr>
<td>Indefinite articles</td>
<td>0.001</td>
<td>Questions -0.033</td>
</tr>
</tbody>
</table>

RQ Structure. With our feature set, linear CRF with subsequences outperforms linear CRF with sequences by an absolute increase of 4% in AUC and of 3% in AP. The results illustrate that modeling a CMV discussion with subsequences bounded by the OH’s participation has practical significance in predicting that OH’s view change, as discussed in Section 3.3.

Although skip-chain CRFs capture more dependencies than linear CRFs, they perform worse. A potential explanation is that the structure is given a priori, not learned. We evaluate additional potential long-range dependencies such as linking comments from the same challenger with skip edges. However, additional edges result in dramatically increased computing time but no improvement in the prediction. Because of the intractability of approximate inference of skip-chain CRFs and the complexity of confounding indicators of dependencies, it is not practical to improve the performance of skip-chain CRFs with hand-crafted rules. We defer to future work to integrate additional layers such as recurrent neural networks to learn dependencies.

One may ask how general CRFs that represent the full-threaded tree structure of a discussion would fare. We conduct an additional test on a tree-structured CRF comparing to skip-chain CRF with different rules for constructing skip edges. Table 8 shows how various rules for constructing edges affect performance. Although tree structure achieves higher AUC-ROC, skip-chain CRF with linked similar comments achieves higher AP. This finding suggests that tree structure predicts more true positives though at the cost of a larger number of false positives than does skip-chain CRF.

Table 8: Performance comparison when constructing skip edges based on different rules.

<table>
<thead>
<tr>
<th>Rule</th>
<th>Tree AP</th>
<th>Reply to AP</th>
<th>Identity AP</th>
<th>Similarity AP</th>
</tr>
</thead>
<tbody>
<tr>
<td>LR</td>
<td>0.09</td>
<td>0.06</td>
<td>0.03</td>
<td>0.14</td>
</tr>
<tr>
<td>Linear</td>
<td><strong>0.78</strong></td>
<td>0.59</td>
<td>0.50</td>
<td>0.70</td>
</tr>
</tbody>
</table>

RQ Benefit. Predicting view changes in real life is challenging because OH’s propensity to award deltas is an unknown prior and data are highly skewed due to the idiosyncrasies of individual OHs. A model that works for pairwise comments with a balanced dataset would not be suitable because real-life data is far from balanced. The proposed sequential model does not require balanced data, and is thus applies better in a natural setting.

An obstacle when evaluating the sequential model on the highly skewed CMV data is that there is no other indicator whether non-$\Delta$

comments are persuasive to some extent. Accordingly, examining the top candidates (predicted positives with high possibility or confidence) rather than exact hits of positives is appropriate. Therefore, we adopt a user model where a user queries for points when an OH’s view may plausibly change during a discussion. We adopt this user model from information retrieval tasks, specifically, of results produced by a search engine in which the top passages matter most. In our setting, we care about if the model can place the most likely comments among the top candidates.

The reciprocal of MRR indicates how many comments a user needs to examine before finding the right one. On CMV, a user needs to read 50 comments on average to find the most persuasive comment if the discussion contains 100 comments. However, an MRR (0.51) for linear CRF with sequences (i.e., an overall discussion) indicates that the model can rank the most persuasive comment among the top two on average.

We conduct statistical tests for better understanding the performance difference between the sequential model and the baseline nonsequential model. Due to the nature of the CMV data, where no assumption may be made about the distribution, we use McNemar’s test to evaluate the significance for which $p < 0.05$ indicates a statistically significant difference between evaluated models and Cohen’s g index (also known as Cohen’s $d$) to evaluate the effect size for which $< 0.15$ indicates a small effect size, $0.15 – 0.25$ indicates a medium effect size, and $> 0.25$ indicates a large effect size [8]. We compare prediction results from LR and linear CRF with subsequences on paired samples. We test on prediction results in the test set and obtain a $p$-value < 0.001 with McNemar’s test and Cohen’s g index of 0.384. The $p$-value indicates a rejection of the null hypothesis and the g index indicates a large effect size, i.e., there is a significant difference between the predictions from LR and the predictions from CRF.

To supplement this result, we analyze the true and false positive rates of the models against discussion dynamics. Figure 2 shows that linear and skip-chain CRFs identify more true positives than logistic regression for longer discussions and for plausible comments that come later in a discussion.

Figure 2: True Positive Rate (TPR) and False Positive Rate (FPR) with respect to discussion dynamics.
5.1 Lessons Learned from Human Study

The above analysis indicates that sequential models demonstrate their ability to capture the cumulative influence and individual perception to some extent. However, the average precision is relatively low comparing to other information retrieval tasks. Therefore, we took a closer look at the human study results to shed some light on the factors that need further investigation in future research.

The human study provides a dataset at a finer granularity than CMV since each comment receives a rating on a scale from multiple annotators rather than a binary label solely from an opinion holder. We obtain a Pearson’s correlation coefficient for raters’ average ratings and binary Δ labels of 0.1645. This weak correlation is consistent with the large variance of raters’ ratings on the same comment and indicates that idiosyncrasies of an individual user greatly affect his or her perception of persuasiveness.

To directly compare the performance of our model to human annotations, we evaluate the best performing CRF model on the human study data and evaluate human annotations by using average ratings as a proxy of the probability for a comment to receive a Δ. As shown in Table 9, the CRF model achieves better performance on all metrics than human annotations. It is notable that human annotations achieve a low AP value similar to the nonsequential models, LR and SVM. In this study, we observe that the low AP value from humans arises primarily because annotators give a greater number of “is-persuasive” ratings (4 or 5) than the actual number of comments with Δs.

Table 9: Performance comparison between human annotations and linear CRF.

<table>
<thead>
<tr>
<th></th>
<th>AP</th>
<th>AUC</th>
<th>MRR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human</td>
<td>0.09</td>
<td>0.77</td>
<td>0.45</td>
</tr>
<tr>
<td>CRF</td>
<td>0.23</td>
<td>0.85</td>
<td>0.81</td>
</tr>
</tbody>
</table>

On the one hand, low average precision is natural for this challenging task that attempts to retrieve the most effective information to change someone’s view from the massive user-generated contents. On the other hand, the results reveal bias in individual perceptions of information. For example, human annotators tend to give high ratings to long comments, as shown in Figure 3.

In addition, we test how our trained CRF model performs if we take human annotations as ground truth for testing. The best performing linear CRF model achieves AUC-ROC of 0.78, AP of 0.32, and MRR of 0.24. The AP is higher than results on the original larger test set, since there are more positives in this ground truth. The experimental results and these findings indicate that the weight of each feature may vary across different settings and the model should be adjusted (retrained) accordingly.

6 UNDERSTANDING PERSUASIVENESS

To overcome the prior belief and bias from researchers, we conduct an additional study (determined to be exempt by our IRB office) to understand the reasoning behind the variance of individual perception of persuasiveness. The study involved 46 participants who are students majoring in computer science. Each participant was randomly assigned two CMV discussion threads. For a selected subset of the comments from its two threads, a participant was asked to rate the persuasiveness of each comment and provide a justification for each rating. Seeing potential reasons helps us investigate why our model yielded a low average precision. Therefore, we select comments for collecting annotators’ reasons if a comment satisfies one of the following criteria: (1) the comment received a Δ from an opinion holder but the CRF model predicted it as not persuasive (false negatives with low possibilities); or (2) the comment did not receive a Δ from an opinion holder but the CRF model predicted it as persuasive (false positives with high possibilities).

We collected 590 reasons for 32 CMV discussions. Since annotators’ ratings do not always align with opinion holders’, we divided the reasons into four groups: (1) 76 comments with Δ and high human ratings, (2) 28 comments with Δ but low human ratings, (3) 249 comments with no Δ but high human ratings, and (4) 237 comments with no Δ and low human ratings. Bigrams that arise frequently in these reasons are shown as word clouds in Figure 4.

The collected reasons from this study provide insights on persuasiveness of comments beyond language usage. The most frequently mentioned reasons for persuasive comments, as shown in Figures 4a and 4c, are providing contradicting knowledge, practical concerns, attacking logic, and examples. It is notable that attacking logic is a frequent strategy that is accepted by human annotators but refused by opinion holders (Figure 4c). For comments that receive low ratings, annotators provide reasons such as inadequate justification, lack of evidence, and not trying to be convincing. Figure 4b suggests that despite the flaws identified by annotators in a comment, opinion holders may find the comment persuasive. Figure 4d indicates features such as the quality of arguments (e.g., detecting a lack of evidence) that a model should incorporate.

7 RELATED WORK

Predicting view change in online argumentation is difficult because it involves cumulative influence, language factors, personality differences, and other confounding factors. Prior research approaches the problem from three main angles.
Wei et al. [38] explore the dynamics of the reply tree of a discussion from the following aspects: (1) we use the sentiments of comments and OH’s replies and (2) dependencies between features in successive comments. Likewise, Jo et al. [19] study the interactions between topics and malleability; they consider the interplay of the original post and a counter-argument but not in the context of the whole discussion. Villata et al. [36] study persuasiveness of arguments and engagement of participants in small groups; however, their study focuses on one participant rather than mutual effects across participants.

A second angle is considering the contextual factors as discussion dynamics and characteristics. For instance, Lukin et al. [21] consider audience factors (i.e., OH’s personality here), which they capture via surveys before a discussion. However, surveys are not an effective method in online discussions. Tan et al. [34] find that the entry order of comments is predictive of their persuasiveness. Wei et al. [38] explore the dynamics of the reply tree of a discussion and users’ reputations. Both works investigate correlations between persuasiveness and each factor separately. However, we posit that factors influence each other and should be estimated jointly. Therefore, we propose a sequential model that uses compound features representing the cumulative influence of a whole discussion from the following aspects: (1) we use the sentiments of an OH’s responses to capture a shift in his or her mindset over time; (2) we encode comments using predictive factors and use the encoded vectors to determine the existence of dependencies between successive and non-successive comments; (3) we represent dependencies as conditional probabilities and examine their cumulative influence on an opinion holder’s mindset.

The third angle focuses on argumentation mining. Analyzing the persuasiveness of arguments is an important direction within argumentation mining. Studies on argumentation mining analyze argument components via formal schemes to analyze the quality and logical connections among the components [5]. For instance, Hidey et al. [14] study claims and premises, and [29] study motions, assertions, and justifications. The associated annotations of persuasiveness or solidity are, in principle, objective [12, 13]. However, in contrast with annotators who may be instructed to reduce bias or be objective, opinion holders on social media are often biased. Thus, we model contextual information and dependencies of comments from a different angle and defer applying knowledge from argumentation mining as future work.

8 CONCLUSIONS

This paper is the first work to raise the problem of identifying a specific point where a view change occurs in an argumentative discussion. This specific problem incorporates real-world factors such as idiosyncrasies of individuals under varying circumstances and information overload on the web. Our results show that modeling the interplay between comments with a sequential model outperforms nonsequential models.

Our approach can potentially be applied to any setting involving online natural language interactions—our emphasis on capturing the dynamic interplay between comments is a central concern in understanding social interaction in general. Future directions include detecting and incorporating argument relations in discussions and evaluating how them in new settings, such as the resolution of conflicts between stakeholders’ goals in design tasks [1, 24].

Based on the findings of Section 6, we identify the following directions for future research.

Categorization of countering strategies. Top reasons, as shown in Figure 4a, indicate a need for classification of countering strategies and understanding the effectiveness of different strategies. A common method to categorize strategies for arguing is to use logos, ethos, and pathos [15]. However, this categorization is from the perspective of rhetorical appeals, and our study indicates that categorization in a finer granularity—which can distinguish contradicting knowledge from practical concerns—is necessary.

Detection of long-distance relations in conversations. Researchers have put effort on identifying relations among argumentation components in discourse [33]. Detecting relations of argument components in conversation is a similar task but requires additional effort on linking content from multiple participants. For instance, as shown in Figure 4b, some comments that earned Δs from opinion holders are marked as unpersuasive by human annotators with reasons “not an argument” or “just a comment.” With a deeper investigation, we observe that these comments often relate to a claim in a previous comment and serve as an argumentation component. This type of long-distance relations is difficult to identify with linguistic indicators, since the transitional words are not stated and require external knowledge.

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