Conversation Derailment Forecasting with Graph Convolutional Networks

Enas Altarawneh
York University
enas@eecs.yorku.ca

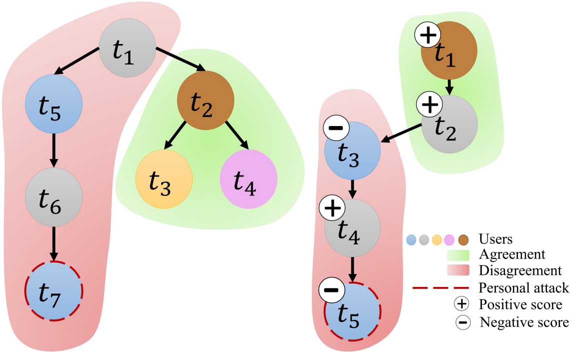
Ameeta Agrawal
Portland State University
ameeta@pdx.edu

Michael Jenkin
York University
jenkin@eecs.yorku.ca

Manos Papagelis
York University
papaggel@eecs.yorku.ca

Abstract

Online conversations are particularly susceptible to derailment, which can manifest itself in the form of toxic communication patterns like disrespectful comments or verbal abuse. Forecasting conversation derailment predicts signs of derailment in advance enabling proactive moderation of conversations. Current state-of-the-art approaches to address this problem rely on sequence models that treat dialogues as text streams. We propose a novel model based on a graph convolutional neural network that considers dialogue user dynamics and the influence of public perception on conversation utterances. Through empirical evaluation, we show that our model effectively captures conversation dynamics and outperforms the state-of-the-art models on the CGA and CMV benchmark datasets by 1.5% and 1.7%, respectively.



(a) Conversation C_{CGA} (b) Conversation C_{CMV}

Figure 1: Conversation derailment examples coming from two benchmark datasets, CGA and CMV; (a) illustrates graph dynamics in a conversation, and (b) illustrates public perception through votes in a conversation. Our FGCN model exploits these features to improve the accuracy of conversation derailment forecasting.

1 Introduction

The widespread availability of chat or messaging platforms, social media, forums and other online communities has led to an increase in the number of online conversations between individuals and groups. In contrast to offline or face-to-face communication, online conversations require moderation to maintain the integrity of the platform and protect users' privacy and safety (Kilvington, 2021). Moderation can help to prevent harassment, trolling, hate speech, and other forms of abusive behavior (Tontodimamma et al., 2021). It can also help to prevent and address conversation derailment.

Conversation derailment refers to the process by which a conversation or discussion is redirected away from its original topic or purpose, typically as a result of inappropriate or off-topic comments or actions by one or more participants. In online conversations, derailment can be exacerbated by the lack of nonverbal cues and the perceived anonymity that can be provided by the internet. Conversation derailment can lead to confusion, frustration, and a lack of productivity or progress in the conversation. Table 1 shows an example conversation taken from the popular CGA benchmark dataset (Zhang et al., 2018). One can observe that there is offensive language used by one of the participants that leads the conversation to derail. The severity of the verbal attack may indicate a prior history between the two participants in previous conversations.

In this research, we examine the problem of *forecasting conversation derailment*. The ability to predict conversation derailment early has multifold benefits: (i) it is *more timely*, as it allows for proactive moderation of conversations (before they cause any harm) due to early warning, (ii) it is *more scalable*, as it allows to automatically monitor large active online communities, a task that is otherwise time-consuming, (iii) it is *more cost-effective*, as it may provide enough aid to limit the number of human moderators needed, and (iv) it may identify upsetting content early and prevent human moderators from being exposed to it.

Early efforts towards automatic moderation fo-

The 7th Workshop on Online Abuse and Harms (WOAH), pages 160–169
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Turn	User	Text	Label
$N-3$	$\mathcal{A}$	*“Proper use of an editor’s history includes fixing errors or violations of Wikipedia policy or correcting related problems on multiple articles."*	
$N-2$	$\mathcal{B}$	*“It’s very clear that you just go to my contributions list and look to see what biography articles I’ve worked on, then you go and look to see if you can find something wrong with them. "*	
$N-1$	$\mathcal{A}$	*“So, what is wrong with fixing things? At the top of my talk page, it says to keep it on your watchlist. "*	
N	$\mathcal{B}$	*“You cannot possibly be too stupid to understand the warning I’m giving you. I’m not going to repeat it."*	**?**

Table 1: A sample conversation from the Conversation Gone Awry (CGA) dataset showing a sequence of text utterances that end with a verbal abuse. Given the conversation context up to $N-1$ turns, the task is to predict whether turn N will be a respectful or offensive statement prior to it being presented leading to derailment (**it is offensive**, in this case).

cused on detecting inappropriate comments once they have occurred. But the utility of such an approach is limited as participants have already been exposed to an abusive behavior and any potential harm has already been caused. The current state-of-the-art approach to predict conversation derailment relies on sequence models that treat dialogues as text streams (Chang et al., 2022; Kementchedjhieva and Søgaard, 2021). However, this approach has limitations, as it ignores the semantics and dynamicity of a multi-party dialogue involving individuals’ intrinsic tendencies and the history of interactions with other individuals.

Based on these observations, we propose a graph-based model to capture multi-party multi-turn dialogue dynamics. In addition, we leverage information associated with conversation utterances that provide public perception on whether an utterance is perceived as positive or negative.

There exist two popular benchmark datasets typically employed for the problem of interest: Conversations Gone Awry (CGA) (Zhang et al., 2018) and Reddit ChangeMyView (CMV) (Chang and Danescu-Niculescu-Mizil, 2019). Both datasets contain multi-party conversations, including the text and an anonymous user ID of each utterance, along with a label annotation on whether the conversation will derail or not. CMV also includes a public vote on each of the utterances that provides the public perception of individuals towards it.

Figure 1a shows an example multi-party conversation from CGA that is not sequential in nature. Note as well that some participants are in either agreement or disagreement of a heated argument. Graph models are more accustomed to represent such dialogue dynamics. Figure 1b shows an example conversation from CMV that shows sample voting scores on each utterance in the conversation that could be related to derailment.

Graph neural networks have been successfully used to model conversations for downstream classification tasks. For example, they have shown promise in forecasting the next emotion in a conversation (Li et al., 2021), a problem similar to that of interest in this work. This motivated us to explore this line of research and make the following contributions:

- We propose a novel model based on a graph convolutional neural network, *the Forecasting Graph Convolutional Network (FGCN)*, that captures dialogue user dynamics and public perception of conversation utterances.

- We perform an extensive empirical evaluation of FGCN that shows it outperforms the state-of-the-art models on the GCA and CMV benchmark datasets by 1.5% and 1.7%, respectively.

The remainder of the paper is organized as follows. Section 2 reviews related work. The technical problem of interest is presented in Section 3. Section 4 presents the proposed models. Section 5 presents the experimental setup, and Section 6 presents the results and a discussion. We conclude in Section 7.

2 Related Work

There has been considerable research attention on the problem of detecting various forms of toxicity in text data. There are methods for identifying cyberbullying (Wiegand et al., 2019), hate speech (Davidson et al., 2017), or negative sentiment (Agrawal and An, 2014; Wang and Cardie, 2016) or lowering the intensity of emotions (Ziems et al., 2022; Xie and Agrawal, 2023). These methods are useful in filtering unacceptable content. However, the focus of these models is on mostly analyzing or classifying already posted harmful texts.

The CRAFT models introduced by Chang et al. (2022) are the first models to go beyond classification of hate speech to addressing the problem of forecasting conversation derailment. The CRAFT models integrate two components: (a) a generative dialog model that learns to represent conversational dynamics in an unsupervised fashion, and (b) a supervised component that fine-tunes this representation to forecast future events. As a proof of concept, a mixed methods approach combining surveys with randomized controlled experiments investigated how conversation forecasting using the CRAFT model can help users (Chang et al., 2022) and moderators (Schluger et al., 2022) to proactively assess and deescalate tension in online discussions.

Extending the hierarchical recurrent neural network architecture with three task-specific loss functions proposed by Janiszewski et al. (2021) was shown to improve the CRAFT models. After pretrained transformer language encoders such as BERT (Devlin et al., 2018) proved to be successful at various NLP tasks, Kementchedjhieva and Søgaard (2021) explored how they can be used for forecasting derailment. The model in this work consists of a BERT checkpoint with a sequence classification (SC) head. Similarly, De Kock and Vlachos (2021) evaluated feature-based and neural models to predict whether disagreements in Wikipedia Talk page conversations will be escalated to mediation by a moderator.

Saveski et al. (2021) studied the relationship between structure and toxicity in conversations on Twitter at individual, dyad, and group level, and found that social relationships among users influence their behaviors. Salehabadi et al. (2022) also studied the differences between toxic and non-toxic conversations on Twitter, highlighting important differences between user engagement and toxicity. While these recent works stress the importance of user characteristics in conversation modeling, to our knowledge, models that incorporate such signals for the task of predicting derailment have remained unexplored.

Here we propose graph-based models for leveraging user-specific information. Graph convolutional neural networks have been used for conversation classification. In one popular application, emotion estimation, the graph model is used to account for speaker related information (Ghosal et al., 2019; Sun et al., 2021). Other work have used similar graph neural networks to forecast emotions (Zhong et al., 2019; Lubis et al., 2019; Liang et al., 2022; Li et al., 2021).

3 Problem Definition

In this section, we formally define the problem of *forecasting conversation derailment*. For a conversation $\mathcal{C} = \{\{t_1, t_2, ..., t_N\}, \{u_1, u_2, ..., u_N\}, \{s_1, s_2, ..., s_N\}\}$ consisting of N turns, the last turn (i.e., the N'th turn) is the potential site of derailment where $l = \{civil, personal\ attack\}$ denotes the label of this turn.

For the ith turn, t_i denotes its text, u_i denotes its user, and s_i denotes an optional score, e.g., number of votes (up-vote/down-vote). An up-vote is a positive impression and a down-vote is a negative impression on the turn utterance. The goal is to forecast the derailment label l of the N'th turn given a conversation $\mathcal{C}$ up to $N-1$ turns (i.e., without any information about the Nth turn).

4 Model for Forecasting Conversation Derailment

In this section, we describe our proposed Forecasting Graph Convolutional neural Network model, (FGCN), visualized in Figure 2.

4.1 Sequential encoding

The input to the model consists of the text t_i, user ID u_i and/or the public perception score s_i for each turn in the conversation $i \in [1, 2, ..., N-1]$, as described below:

Textual input — the input consists of an encoding of the turn text t_i using BERT embeddings extracted after fine tuning as described in Kementchedjhieva and Søgaard (2021), resulting in the sequential encoding of the text as vector $t_i^{'}$.

User ID input — the input consists of an encoding of the user ID as a randomly initialized vector u_i, where each user has a unique vector; we use BiLSTM sequential encoding to obtain the utterance user ID vectors $u_i^{'}$. We use unique randomly initialized vectors to avoid privacy issues that may arise using actual IDs.

Public perception input — the input consists of a popularity score where the up-votes on a turn is subtracted by the down-votes on the same. To obtain the score vector s_i we use equal depth binning to capture three levels of popularity for positive

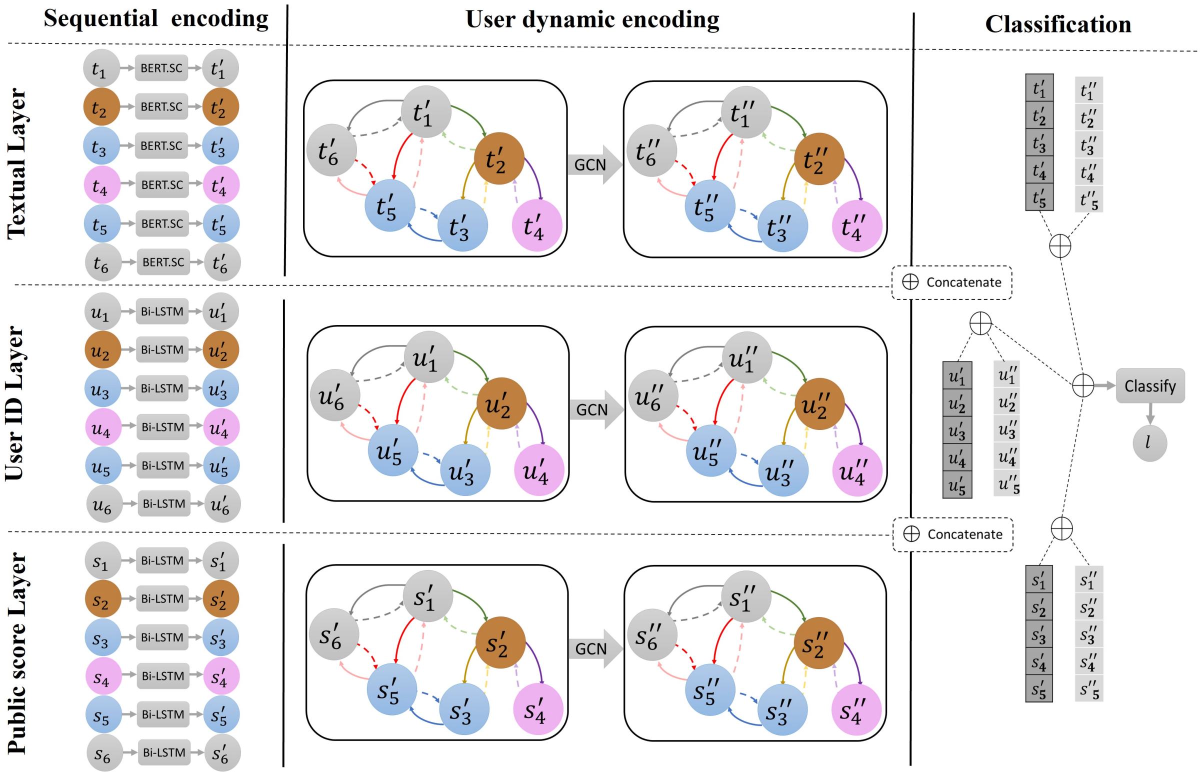
Sequential encoding
User dynamic encoding
Classification
Textual Layer
User ID Layer
Public score Layer
BERT.SC
Bi-LSTM
GCN
Concatenate
Classify
t_1 t_2 t_3 t_4 t_5 t_6
t'_1 t'_2 t'_3 t'_4 t'_5 t'_6
t''_1 t''_2 t''_3 t''_4 t''_5 t''_6
u_1 u_2 u_3 u_4 u_5 u_6
u'_1 u'_2 u'_3 u'_4 u'_5 u'_6
u''_1 u''_2 u''_3 u''_4 u''_5 u''_6
s_1 s_2 s_3 s_4 s_5 s_6
s'_1 s'_2 s'_3 s'_4 s'_5 s'_6
s''_1 s''_2 s''_3 s''_4 s''_5 s''_6
l

Figure 2: The FGCN model architecture.

scores and three levels of unpopularity for negative scores. We use a BiLSTM sequential encoder on s_i resulting in utterance public perception vectors $s_i^{'}$.

4.2 Graph Construction

For a given conversation, the output of the sequential encoder for each one of these input types $t_i^{'}$, $u_i^{'}$ and $s_i^{'}$ is used to initialize the vertices in the homogeneous graphs shown in Figure 2. The vertices in the graphs represent the turns in the conversation. Each graph $G_x = (V, E, R, W)$, for each type of input $x \in \{t, u, s\}$, is constructed with vertices $v_i \in V$, $r_{ij} \in E$ is the labeled edges between v_i and v_j, the edge labels (relations) $\in R$ and α_{ij} is the weight of the labeled edge r_{ij}, with $0 \leq \alpha_{ij} \leq 1$, where $\alpha_{ij} \in W$, $i \in [1, 2, ..., N-1]$ and $j \in$ the set of all neighboring vertices to v_i.

For each conversation we construct three types of graphs; a text-based G_t, a user-based G_u and a public perception score-based G_s. In G_t, each conversation turn is represented as a vertex $v_i \in V$ and is initialized with the textual sequentially encoded feature vector $t_i^{'}$, for all $i \in [1, 2, ..., N-1]$. In G_u each vertex is initialized with a utterance user ID vector $u_i^{'}$, for all $i \in [1, 2, ..., N-1]$ provided by the sequential encoder. Similarly, in G_s each vertex is initialized with a utterance public score vector $s_i^{'}$, for all $i \in [1, 2, ..., N-1]$ provided by the sequential encoder.

User to user relationship edge construction. We establish the direct user to user relationship in a conversation through the edge construction of each graph. This results in efficient graph modeling with less complexity compared to complete graphs. Figure 3 shows an example graph edge construction for a given conversation. In user-to-user relationship edge construction, each vertex v_i representing a turn in the conversation has directed edges connecting it to its preceding (parent) and succeeding comments/turns (children). Same user comments (turns) are also connected through directed edges. The user-to-user relation $\in R$ of an edge r_{ij} is set based on the user-to-user dependency between user u_i (of turn v_i) and user u_j (of turn v_j).

For example, in Figure 3, there are four users, so the set of edge labels R has the relation types shown under user-to-user dependency. Furthermore, as the graph is directed, two vertices can have edges in both directions with different relations. We use this to represent the past (backward) and future (forward) temporal dependency between the vertices, shown as temporal user dependency. The edge weights are set using a similarity based attention module. The attention function is computed such

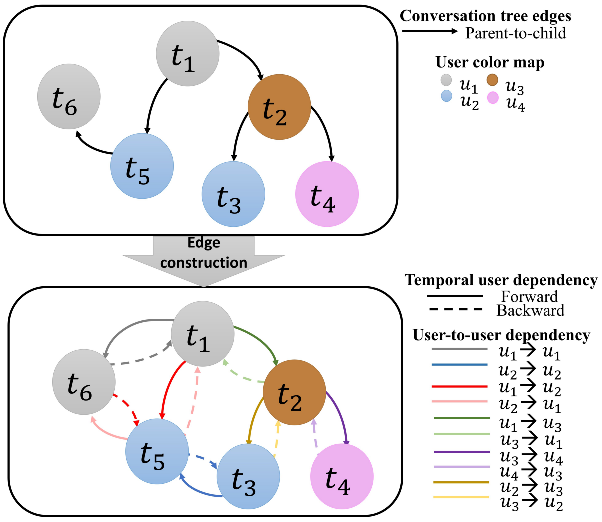

Figure 3: An example graph edge construction for the given conversation with user-to-user and temporal dependency.

that, for each vertex, the incoming set of edges has a sum total weight of 1. The weights are calculated as, $\alpha_{ij} = softmax(v_i^T W_e[v_{j_1}, ..., v_{j_m}])$, for j_k, where $k = 1, 2, .., m$, for the m vertices connected to v_i, ensuring the vertex v_i receives a total weight contribution of 1.

4.3 Feature Transformation

The sequentially encoded text features $t_i^{'}$, the user features $u_i^{'}$, and the public perception features $s_i^{'}$ of the graph network are transformed from user dynamic independent into user dynamic dependent feature vectors using a two-step graph convolution process employed by Ghosal et al. (2019). In the first step, a new feature vector is computed for each vertex in all three graphs by aggregating local neighbourhood information:

$$u_i^{''} = \sigma(\sum_{r \in R} \sum_{j \in N_i^r} \frac{\alpha_{ij}}{c_{i,r}} W_r\, u_j^{'} + \alpha_{ii} W_0\, u_i^{'}),$$

$$t_i^{''} = \sigma(\sum_{r \in R} \sum_{j \in N_i^r} \frac{\alpha_{ij}}{c_{i,r}} W_r\, t_j^{'} + \alpha_{ii} W_0\, t_i^{'})$$

$$s_i^{''} = \sigma(\sum_{r \in R} \sum_{j \in N_i^r} \frac{\alpha_{ij}}{c_{i,r}} W_r\, s_j^{'} + \alpha_{ii} W_0\, s_i^{'})$$

for $i = 1, 2, ..., N-1$, where, α_{ii} and α_{ij} are the edge weights, and N_i^r is the neighbouring indices of vertex i under relation $r \in R$. $c_{i,r}$ is a problem specific normalization constant automatically learned in a gradient based learning setup. Σ is an activation function such as ReLU, and W_r and W_0 are learnable parameters of the transformation. In the second step, another local neighbourhood based transformation is applied over the outputs of the first step, as follows:

$$u_i^{''} = \sigma(\sum_{j \in N_i^r} W\, u_j^{''} + \alpha_{ii} W_0\, u_i^{''}),$$

$$t_i^{''} = \sigma(\sum_{j \in N_i^r} W\, t_j^{''} + \alpha_{ii} W_0\, t_i^{''})$$

$$s_i^{''} = \sigma(\sum_{j \in N_i^r} W\, s_j^{''} + \alpha_{ii} W_0\, s_i^{''})$$

for $i = 1, 2, ..., N-1$, where, W and W_0 are transformation parameters, and σ is the activation function. This two step transformation accumulates the normalized sum of the local neighbourhood.

4.4 Forecasting Derailment

To form the final turn representation, the sequential encoded vectors $t_i^{'}$, $u_i^{'}$ and $s_i^{'}$, and the user dynamic encoded vectors $t_i^{''}$, $u_i^{''}$ and $s_i^{''}$ are concatenated for each turn i in a conversation to form:

$$g_i = [t_i^{'}, u_i^{'}, s_i^{'}, t_i^{''}, u_i^{''}, s_i^{''}]$$

Then, each g_i, $i \in \{1, 2...., N-1\}$ is concatenated to form a representation of the conversation C:

$$C^{'} = [g_1, g_2..., g_{N-1}]$$

Finally, $C^{'}$ is fed to a classifier with a linear layer, a full connected network and a sigmoid activation function, as described by Ghosal et al. (2019), to obtain the label $\hat{l}$ of each conversation C.

4.5 Model variants

To understand the effect of each type of input on forecasting derailment, we create variants of our model where the types of input are gradually included. The following is a more detailed description of the models used in this work.

FGCN-T — this variant of the model constructs one graph using the output of the sequential encoder on the textual data $t_i^{'}$. It is created for both CGA and CMV, as both contain the textual data. FGCN-T uses only the textual layer shown in Figure 2. At classification it concatenates $t_i^{'}$ with the result of the GCN feature transformation $t_i^{''}$ during user dynamic encoding.

Dataset	Input			Train	Val	Test
	t	u	s			
CGA	✓	✓	✓	2508	840	840
CMV	✓	✓	×	4106	1368	1368

Table 2: Statistics of the datasets. t denotes text input, u denotes user ID input and s denotes public perception score input. All splits are balanced between the two classes.

FCGN-TU — this variant of the model constructs two graphs using the output of the sequential encoder, one for the textual output $t_i^{'}$ and the other for the user ID output $u_i^{'}$. It is created for both CGA and CMV, as both contain the textual and user ID data. FGCN-TU uses the textual and user ID layer shown in Figure 2. At classification it concatenates $t_i^{'}$ and $u_i^{'}$ with the result of the GCN feature transformation $t_i^{''}$ and $u_i^{''}$ during user dynamic encoding.

FGCN-TS — this variant of the model constructs two graphs using the output of the sequential encoder, one for the textual output $t_i^{'}$ and the other for the public perception score output $s_i^{'}$. It is created for CMV, as only CMV contains the public perception data. FGCN-TS uses the textual and public score layer shown in Figure 2. At classification it concatenates $t_i^{'}$ and $s_i^{'}$ with the result of the GCN feature transformation $t_i^{''}$ and $s_i^{''}$ during user dynamic encoding.

FGCN-TSU — this variant of the model constructs three graphs using the output of the sequential encoder, one for the textual output $t_i^{'}$, the user ID output $u_i^{'}$ and the public perception score output $s_i^{'}$. It is created for CMV, as only CMV contains the public perception data. FGCN-TSU uses all layers shown in Figure 2. At classification it concatenates $t_i^{'}$, $u_i^{'}$ and $s_i^{'}$ with the result of the GCN feature transformation $s_i^{''}$ and $s_i^{''}$ during user dynamic encoding.

5 Experimental Setup

5.1 Datasets

We use two datasets for the task of forecasting derailment in conversations. Some statistics of the datasets are summarized in Table 2.

Conversations Gone Awry (CGA) dataset (Zhang et al., 2018) was extracted from Wikipedia Talk Page conversations. The conversations were sampled from WikiConv (Hua et al., 2018) based on an automatic measure of toxicity that ranges from 0 (not toxic) to 1 (is toxic). A conversation is extracted as a sample of derailment if the Nth comment in it has a toxicity score higher than 0.6 and all the preceding comments have a score lower than 0.4. Conversations having all comments with a toxicity score below 0.4 are extracted as samples of non-derailment. This set of conversations is further filtered through manual annotation to determine whether after an initial civil exchange a personal attack occurs from one user towards another. The conversations include the turn with the personal attack. This means all $N-1$ turns in a conversation are civil and the N'th one is either civil or contains a personal attack. The dataset also contains additional information about each comment in the conversation such as the user posting the comment and the ID of the parent comment that this comment was a reply to.

Reddit ChangeMyView (CMV) dataset (Chang and Danescu-Niculescu-Mizil, 2019) was extracted from Reddit conversations held under the ChangeMyView subreddit. Conversations were identified as derailed if there was a deletion of a turn by the platform moderators. This could have been done under Reddit's Rule: "Don't be rude or hostile to other users." Unlike CGA, there is no control to ensure that all the preceding comments to the last one would be civil, resulting in some noise in the data. The dataset also contains additional information about each comment in the conversation such as the user posting the comment, the ID of the parent comment that this comment was a reply to, and a votes score (i.e., the number of up-votes minus the number of down-votes).

5.2 Evaluation Metrics

Following prior work, we report the performance of the models in terms of accuracy (Acc), precision (P), recall (R), and F1-score. We also report the forecast horizon H introduced by Kementchedjhieva and Søgaard (2021), which is the mean of the turns in which the first detection of derailment occurred for the set of conversations that derail.

5.3 Baselines

Our FGCN model and its variants are evaluated against the state-of-the-art methods below.

CRAFT (Chang and Danescu-Niculescu-Mizil, 2019) is a model with a hierarchical recurrent neural network architecture, which integrates a generative dialog model that learns to represent conver-

Traning	Model	CGA				CMV			
		Acc	P	R	F1	Acc	P	R	F1
Static	CRAFT	64.4	62.7	71.7	66.9	60.5	57.5	81.3	67.3
	BERT·SC	64.7	61.5	79.4	69.3	62.0	58.6	82.8	68.5
	FGCN-T	66.4	63.0	79.5	70.3	62.9	59.2	83.0	69.1
	FGCN-TU	66.9	63.3	80.2	**70.8**	63.2	59.5	83.0	69.3
	FGCN-TS	-	-	-	-	64.2	60.3	83.2	69.9
	FGCN-TSU	-	-	-	-	64.7	60.7	83.3	**70.2**
Dynamic	BERT·SC+	64.3	61.2	78.9	68.8	56.5	56.0	73.2	61.7
	FGCN-T+	65.7	62.2	79.7	69.9	62.1	58.5	82.0	68.3
	FGCN-TU+	65.9	62.4	80.2	**70.2**	62.7	58.8	82.7	68.8
	FGCN-TS+	-	-	-	-	62.9	59.2	82.9	69.1
	FGCN-TSU+	-	-	-	-	63.5	59.7	83.1	**69.5**

Table 3: Experimental results for forecasting conversation derailment. Best F1-score are in bold.

sational dynamics in an unsupervised fashion, and a supervised component that fine-tunes this representation to forecast future events. This model is trained statically. Static training entails that all $N-1$ turns $\{t_1, ..., t_{N-1}\}$ of a conversation of N turns are used as one input instance.

BERT·SC (Kementchedjhieva and Søgaard, 2021) is a model consisting of the BERT checkpoint with a sequence classification (SC) head, trained statically, i.e. in the same manner as CRAFT.

BERT·SC+ (Kementchedjhieva and Søgaard, 2021) similar to BERT·SC consists of the BERT checkpoint with a sequence classification (SC) head, but is instead trained *dynamically*. Dynamic training entails that a conversation of N turns $\{t_1, ..., t_{N-1}\}$ with label l is mapped to multiple training samples, each representing a different phase of the conversation unfolding, but all labeled with the same label l. So a conversation of N turns is converted into $N-1$ training instances samples $\{t_1\}, \{t_1, t_2\}, ..., \{t_1, ..., t_{N-1}\}$ instead of just the one $\{t_1, ..., t_{N-1}\}$.

5.4 Implementation

We use two training paradigms, static and dynamic: In **static training**, for each conversation we use one training instance with all turns $\{\{t_1, ..., t_{N-1}\}$, $\{u_1, ..., u_{N-1}\}$ and/or $\{s_1, ..., s_{N-1}\}\}$ as input. In **dynamic training**, we use multiple instances of each conversation, by varying the last turn used in each training instance. So, we use $\{t_1$, u_1 and/or $s_1\}$ as an instance, $\{\{t_1, t_2\}$, $\{u_1, u_2\}$, and/or $\{s_1, s_2\}\}$ as another instance, and so on until the last instance $\{\{t_1, ..., t_{N-1}\}$, $\{u_1, ..., u_{N-1}\}$ and/or $\{s_1, ..., s_{N-1}\}\}$. So we have $N-1$ instances of each conversation. We denote all dynamically trained models with an added "+" at the end of the model name.

At inference time, the model is tested dynamically, i.e., by using turn $\{t_1$, u_1 and/or $s_1\}$ as input, and making a prediction $\hat{l_1}$, then using turns $\{\{t_1, t_2\}$, $\{u_1, u_2\}$, and/or $\{s_1, s_2\}\}$, and making a prediction $\hat{l_2}$, and so on until $N-1$ predictions have been accumulated. The overall predicted label for a given conversation is then obtained as $\hat{l} = \max_{i=1}^{N-1} \hat{l_i}$.

Our models used the same BERT implementation (i.e., `bert-base-uncased`) as in the baseline models (Kementchedjhieva and Søgaard, 2021), for our textual sequential encoding, to ensure a comparable evaluation setting. However, it is worth mentioning that any pretrained language model can be used. The graph neural network component described in this work is implemented with settings similar to that reported by Ghosal et al. (2019). The results are reported as an average over 10 different runs with random initialization, to account for variance in model performance.

6 Results and Discussion

In the forecasting conversation derailment experiment we report the results of the static and dynamic training of our model and its variants and compare with baselines. In the analyzing mean forecast horizon experiment we show how early each model can forecast derailment.

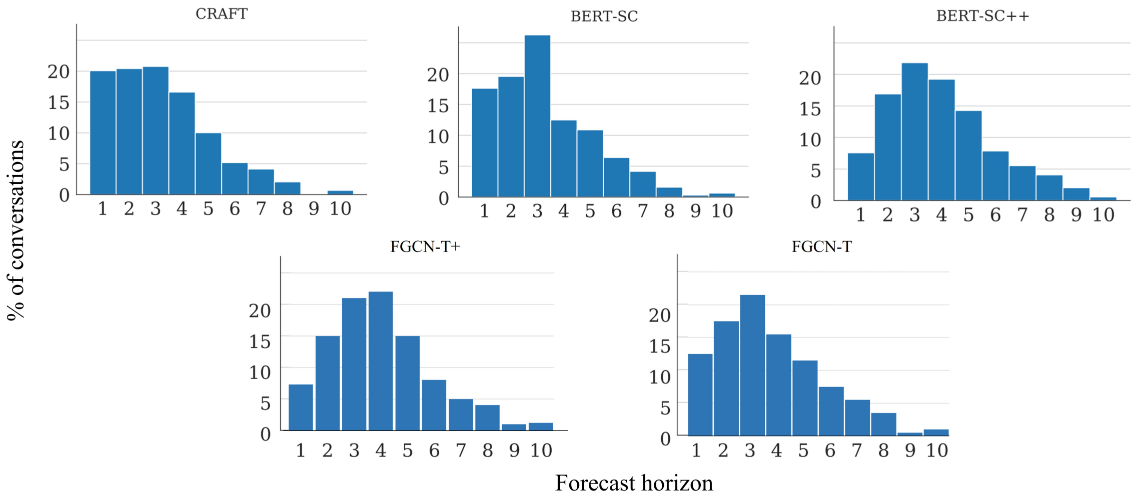

Figure 4: Forecast horizon on the CGA dataset with a model drawn at random from among the 10 available ones. A horizon of 1 means that an upcoming derailment was only predicted on the last turn before it occurred.

6.1 Forecasting Conversation Derailment

The results in Table 3 show that across both the datasets, FGCN-T, our text based graph neural network model, outperforms baseline models when given similar text input. FGCN-TU, which explicitly uses user ID's in addition to text data, further improves the results for both the datasets. FGCN-TS, which uses text and public perception data in the CMV dataset, brings similar improvements. Furthermore, the results of the FGCN-TSU model, which uses text, user and public perception data, indicate that incorporating all three features when available can be beneficial. Note that CGA does not provide any public perception data and was excluded from this experiment.

Statically trained models outperform their corresponding dynamically trained models. However, our dynamically trained models outperform both statically and dynamically trained baselines.

Taken together, these results indicate that modeling conversations using a graph neural network improves the models' forecasting F1-score. They also demonstrate that this modeling framework is flexible and allows for incorporating more types of data that may be beneficial. For instance, future work could investigate the potential benefit of integrating explicit emotion or sentiment values (Babanejad et al., 2019; Agrawal et al., 2016) into derailment forecasting models.

6.2 Analyzing Mean Forecast Horizon

How early can the model forecast the derailment? To answer this question we calculate the forecast horizon H, the mean of the turn in which the first detection of derailment occurred for the set of conversations that derail. A forecast horizon H of 1 means that a derailment coming up on turn N was first detected on turn $N-1$. A longer forecast horizon (i.e., a higher H) allows for earlier interventions and potentially allows moderators to delete the upcoming personal attack as soon as it appears on their platform to avoid any form of escalation. Models that are able to detect a potential intervention earlier have a clear advantage.

	CGA	CMV
CRAFT	2.36	4.01
BERT·SC	2.60	3.90
BERT·SC+	<u>2.85</u>	<u>4.06</u>
FGCN-T	2.73	4.03
FGCN-T+	**2.96**	**4.12**

Table 4: Experimental results of mean forecast horizon (H).The best result is shown in bold whereas the second best result has been underlined.

In Table 4 we report the results of the mean forecast horizon H. The results show that our model FGCN-T+ with its dynamic training provides the earliest overall forecasting of derailment with a mean H of 4.12 for CMV, and 2.95 for CGA. Followed by another dynamically trained model BERT.SC+. For the statically trained models (CRAFT, BERT.SC, and FGCN-T), FGCN-T has the best performance as it seems to be able to better model the dynamic relationships between the users of the turns with its graph model, obtaining a mean H of 4.03 for CMV and, 2.73 for CGA.

We perform further analysis of the forecast horizon results for CGA. Figure 4 illustrates the forecast horizon of the different models. In earlier work, both CRAFT and BERT·SC, the models make a prediction with a forecast horizon $H > 1$ turn at a high rate. Only 20% of CRAFT's forecasts and 17.5% of BERT·SC's forecasts came on the last turn before the derailment. Turning to BERT·SC+, we see that dynamic training has helped in shifting a lot of the density from $H <= 3$ towards $H > 3$. The last-minute forecasts for BERT·SC+ model come at a rate of only 7.5%. FGCN-T and FGCN-T+ uses BERT.SC in its sequential textual component and combines it with a graph component. FGCN-T was also able to shift density from $H <= 3$ towards $H > 3$ even though it was trained statically, indicating that the result was due to the graph modeling. The dynamiclly trained FGCN-T+ outperforms all by shifting even more density towards $H > 3$ and a last minute forecast at a rate of only 7%.

7 Conclusion

Unlike previous models which were based on simpler sequence models, FGCN is built on a graph convolutional neural network and is able to capture the dynamics of multi-party dialogue, including user relationships and public perception of conversation statements. FGCN performed significantly better than state-of-the-art models on two widely used benchmark datasets, CGA and CMV. Conversation derailment is a significant issue that frequently and severely impacts our online social interactions, whether in casual settings or more formal contexts such as online learning or remote work. The ability to accurately predict derailment has the potential to enhance the effectiveness of moderation and thus protect individuals who are vulnerable to emotional abuse or harm and improve the overall quality of online interactions.

Limitations

Graph models require four or more utterances to form meaningful conversation connections and model their dynamics. In some cases, conversations that derail are not sufficiently long and may be best modeled by simpler sequential models. Any of these models will work best with asynchronous conversations where there is a time lag between the turns to allow for moderation after forecasting.

Ethics Statement

In our paper, we focus on the problem of forecasting conversation derailment. The practical employment of any such system on online platforms has potential positive impact, but several things would be important to first consider, including whether forecasting is fair (Williamson and Menon, 2019), how to inform users about the forecasting (in advance, and when the forecasting affects users), and finally what other action is taken when derailment is forecast. Please refer to (Kiritchenko et al., 2020) for a related overview of such considerations, in the context of abusive language detection.

Acknowledgments

We are grateful to the anonymous reviewers for their insightful feedback. The financial support of NSERC, the NCRN, VISTA and the IDEaS network is gratefully acknowledged.

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