A Discourse Aware Sequence Learning Approach for Emotion Recognition in Conversations

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Abstract

The expression of emotions is a crucial part of daily human communication. Modeling the conversational and sequential context has seen much success and plays a vital role in Emotion Recognition in Conversations (ERC). However, existing approaches either model only one of the two or employ naive late-fusion methodologies to obtain final utterance representations. This paper proposes a novel idea to incorporate both these contexts and better model the intrinsic structure within a conversation. More precisely, we propose a novel architecture boosted by a modified LSTM cell, which we call DiscLSTM, that better captures the interaction between conversational and sequential context. DiscLSTM brings together the best of both worlds and provides a more intuitive and efficient way to model the information flow between individual utterances by better capturing long-distance conversational background through discourse relations and sequential context through recurrence. We conduct experiments on four benchmark datasets for ERC and show that our model achieves performance competitive to state-of-the-art and at times performs better than other graph-based approaches in literature, with a conversational graph that is both sparse and avoids complicated edge relations like much of previous work.

We make all our codes publicly available on GitHub.

Index Terms: emotion recognition, discourse learning, graph learning

1. Introduction

Emotion recognition in conversations (ERC) is an emerging field of study, where the primary task is to identify the emotion behind each utterance in a conversation, with many datasets released recently [1,2,3,4] and researchers finding potential applications in areas of emphatic dialog systems [5], improved human-computer interaction [6] and social media opinion mining [7].

The implicit emotion hidden behind an utterance is influenced by several factors, including acoustic cues, facial expressions, and the semantic properties of the utterance. Moreover, we acknowledge the fact that the emotion of a utterance that is too short might be challenging to identify in isolation [8]. Thus, imputing extra knowledge into the system by effectively modeling sequential and conversational context becomes increasingly important. The sequence of turns in a conversation plays an important role, and modeling sequential context has been seen as effective in capturing the conversational context by knowing about the past utterances. In the past, researchers have successfully employed LSTM and GRU-based networks with much success [9], however these cells do not effectively capture long-range dependencies [10] and the global knowledge about all the past utterances might not be useful to model emotions. To alleviate this problem and better capture long-range conversational context in conversations where two or more entities participate in a dialogue, researchers have proposed the use of graph neural networks (GNNs) [8]. Some major problems with this approach too include in-efficient dependency relations between individual turns or missing sequential context like LSTMs as GNNs consider all utterances equally while modeling. Prior work on this mostly employs late fusion of sequential and graph representations [8,11] which gives rise to two main problems; 1) Uncertainty related to the quality of long-range structured dependencies captured by graphs because these relations are hand-engineered or based on naive assumptions (in our case, the relations are predicted from another neural model, which induces more uncertainty). 2) No learning is involved in determining how much of both information to keep or discard while determining the emotion behind an utterance. We acknowledge that though emotions behind individual utterances in a conversation are structurally dependent upon other background utterances in the past, it is the sequence of the utterances that helps make sense out of the entire conversation.

Another problem with most existing GNN-based methods for ERC is that they focus on local or speaker relations between utterances and fail to incorporate the structured distant relations between utterances in the conversation. However, discourse dependencies between utterances provide a straight-forward way to capture both adjacent and distant cues for ERC [11].

To alleviate the above problems, in this paper, we build on the notion that both long-range conversational background and nearby context are equally crucial for ERC, and propose a robust approach to modeling both by introducing a unique LSTM cell, DiscLSTM, or Discourse-aware LSTM, which incorporates discourse-aware structured graph information into sequential recurrence-based learning. More precisely, our LSTM cell takes two inputs: 1) The high-level utterance representation of the particular turn in a conversation and 2) The graph-encoded discourse-aware representation for the utterance at that turn and introduces a new cell-state and gating mechanism which dynamically learns the amount of information to be retrieved from both representations. Specifically, we now learn the linear sequential context aided by the structured graph-encoded discourse context. More details about DiscLSTM can be found in Section 3. To sum up, our contributions are as follows:

- We propose to learn the linear sequential context of utterances in a conversation aided by dependency-based discourse relations between utterances in the conversation for the task of ERC. To achieve this we introduce...
DiscLSTM, which according to us is a more reasonable and appropriate way to incorporate both sequential and structured utterance-level dependencies for ERC.

- We conduct extensive experiments on four ERC benchmarks and show that our proposed architecture DiscLSTM achieves comparable performance with other state-of-the-art sequence and graph-based models without the use of external knowledge or complicated edge relations.

2. Related Work

The task of Emotion Recognition (ER) aims at identifying emotional states expressed by humans in different turns during a conversation. ER as a downstream task has been thoroughly studied in the past, including systems that consider each utterance separately or consider the context of the conversation. This section will primarily discuss the latter, divided into the two dominant categories in the literature that researchers have used to model the conversational context.

2.1. Graph-based Models

One of the first works in this space was the DialogueGCN [3], which treats each dialogue as a graph, with vertices as individual utterances, and edges connecting a vertex with it’s past and future turns. An improvement over DialogueGCN was RGAT [12] which adds positional encodings to the DialogueGCN framework. ConGCN [13] on the other hand also takes speakers as vertices in addition to individual utterances, which makes it consider the whole ER dataset as a single graph. DAG-ERC [14] uses a Directed Acyclic Graph which combines the benefits of graph and recurrence models with it’s structural properties. Moreover, DAG-ERC also makes meaningful and reasonable assumptions while constructing the graph by 1) removing the link of an utterance in a dialogue to future utterances and 2) by imputing remote information for modeling conversational context by introducing another edge to the speakers previous utterance. Very recently MMGCN [15] proposed fusing information from multiple modalities by the use of spectral domain GCN to encode the multimodal contextual information. The work closest to our work is [11], where the authors use discourse relations between utterances to build a conversational graph and show that ER in both multi-party and two-party conversations benefit from conversational discourse structures. Some other approaches include KET [16] makes use of hierarchical transformers with external knowledge and DialogXL [17] dialog-aware self-attention.

2.2. Recurrence-based Models

Under this category, ICON [18] and CMN [19] both employ a gated recurrent unit (GRU) and memory networks. HiGRU [20] on the other hand employs two GRUs, one of which acts as an utterance encoder and the other as a conversation encoder. DialogRNN [6] proposes to model dialog dynamics with several RNNs. The latest and the most recent work in this space is COSMIC [21], which is very similar to DialogRNN in its neural network architecture and additionally adds external commonsense knowledge thereby improving ERC performance.

2.3. Discourse Parsing

Discourse parsing in conversations has been extensively studied and proven to be effective for various dialogue understanding tasks like identifying the decisions in multi-party dialogues [22] or detecting salient content in email conversations [23]. As a result, in this paper, we also propose to model the rich structure in human conversations by incorporating discourse relations between utterances in a dialogue. Incorporating graph-encoded discourse relations for NLP tasks, though currently very under-explored, has seen success in tasks like ERC [11], abstractive conversation summarization [24] and machine reading comprehension [25]. Intuitively, discourse relations help the system to better encode unstructured conversations and allow the model to concentrate on the most salient utterances to generate more precise predictions.

3. Proposed Method

3.1. Problem Formulation

Suppose there are m participants \{p_1, p_2, p_3, \ldots, p_m\} in a conversation or dialogue with n number of utterances \{e_1, e_2, e_3, \ldots, e_n\}, where utterance e_i is uttered by p_i. \(p(.)\) denotes the mapping of between an utterance and it’s speaker. The primary objective of ERC is to predict the emotion label y_i for utterance u_i based on the context of the dialogue to which u_i belongs. We denote a dialogue as \(U_j\), where utterance u_i \in U_j and \(D = \{U_1, U_2, \ldots, U_T\}\) where dataset D has a total of T dialogues.

3.2. Utterance-level feature extraction

We formulate each conversation \(U_j\) as a graph and treat each utterance embedding u_i \in U_j as a node in the graph. In lines with prior-art [8] [14], we use the RoBERTa large transformer model, fine-tuned on the task-specific ERC dataset to extract contextualized features \(u_i \in \mathbb{R}^{768}\) for each individual utterance e_i in the dialogue. More precisely, similar to [8], we add a /CLS/ token at the beginning of each tokenized utterance we...
Motivated by the fact that utterances from individual speakers in a conversation do not occur in isolation, but instead occur in conjunction and in relation to each other, and the emotion expression by an individual speaker at each turn is at large dependent on the conversational discourse context \[26, 27\], similar to \[11\], we resort to modelling the entire conversation as a structured graph network with individual utterances as nodes and connected to each other by their conversational discourse relations. Additionally, this is more efficient than sliding window or fully connected graphs used in literature \[8\].

We view each utterance as an EDU (Elementary Discourse Unit) and use the discourse relation types defined in \[28\]. To extract discourse relations in a conversation, we first train a state-of-the-art model \[29\] on a human-annotated multi-party dialogue corpus \[28\]. We then utilize this trained parser to predict the discourse relations within the conversations in our 4 ERC datasets. Examples of relations extracted are shown in Fig. 1.

During link prediction and relation classification, the model not only utilizes local information that represents the concerned EDUs, but also global information that encodes the EDU sequence and the discourse structure that is already built at the current step. Formally put, for each conversation, we construct a discourse graph \( G = (V, E) \), where \( V = \{v_1, v_2, v_3, \ldots, v_n\} \) are the nodal representations of the utterances \( \{u_1, u_2, u_3, \ldots, u_n\} \) and \( E \in \mathbb{R}^{n \times n} \) is the adjacency matrix denoting edge relation, where \( E[i][j] = 1 \) if there is a discourse relation between utterance \( i \) and \( j \).

### 3.3. Graph Construction from the Conversation

![Graph Network](image)

3.4. Temporal Information Flow in Graph Layers

For encoding discourse relations in a conversation, we use a Graph Attention Network (GAT) \[30\] with the information flow through layers inspired by \[31\]. To feed our contextualised RoBERTa-based utterance embedding \( e_i \in \mathbb{R}^{1024} \) to our graph network, we first down-project \( e_i \) to \( g_i^1 \), where a \( g_i^1 \in \mathbb{R}^{300} \) via a full-connected layer \( f(.) \). This operation can be denoted as:

\[
G^1 = f(U) = \{g_1^1, g_2^1, g_3^1, \ldots, g_n^1\} \tag{1}
\]

where \( G^1 \) is the graph-encoded representation of our utterance output by the first layer in the graph. Our graph information propagation step from the hidden layer information of the text to the graphical encoding is inspired by \[31\]. For each utterance embedding \( g_i \), the attention weights between \( g_i \) and its predecessors are calculated by using \( g_i \)'s hidden state at the \((l - 1)\)-th layer and the nodes \( j \in N_i \) in the current \((l)\)-th. Formally, we find the attention weights of utterance \( u_i \)'s hidden value with the above-mentioned nodes in the following manner using a GAT layer:

\[
\alpha_{ij}^l = \text{softmax}_{j \in N_i}(W_{ij}^l[|g_j^l|][g_i^{l-1}]) \tag{2}
\]

where \( W_{ij}^l \) are the learnable parameters and \( || \) represents concatenation operation.

We finally gather or accumulate the information using the weights calculated above and get the subsequent layer information:

\[
g_i^l = \sum_{j \in N_i} \alpha_{ij}^l g_j^l + g_i^{l-1} \tag{3}
\]
We use the final graph layer embedding after multiple information propagation steps in the graph network and obtain $G^t = \{g_1, g_2, g_3, \ldots, g_t\}$ and the contextualized embeddings from the RoBERTa for our next step.

### 3.5. Bi-Directional DiscLSTM Cell

In order to better integrate both the sequential and discourse context, and to dynamically learn the relative importance of each the graph encoded utterance representation for modeling a conversation, we propose DiscLSTM. DiscLSTM builds on the basic LSTM cell\(^\text{[32]}\) and takes as inputs previous cell state $c_{t-1}$, previous hidden state $h_{t-1}$, current cell input $u_t$, and an additional graph-encoded utterance representation $g_t$. The cell outputs the current cell state $c_t$ and the current hidden state $h_t$. The cell representation can be seen in Fig. 3. The following equations represent the propagation of information inside the DiscLSTM cell:

$$f_t = \sigma (W_f u_t + U_f h_{t-1} + Q_f g_t + b_f)$$
$$o_t = \sigma (W_o u_t + U_o h_{t-1} + Q_o g_t + b_o)$$
$$i_t = \sigma (W_i u_t + U_i h_{t-1} + b_i)$$
$$p_t = \sigma (W_p u_t + Q_p g_t + b_p)$$
$$c_t = \tanh (W_c u_t + U_c h_{t-1} + b_c)$$
$$\hat{h}_t = \sigma (W_{\hat{h}} u_t + U_{\hat{h}} h_{t-1} + b_{\hat{h}})$$
$$h_t = o_t \odot \tanh (c_t)$$

We use the utterance representation $u_t$ and the graph-encoded representation $g_t$ as input to the bi-directional DiscLSTM which then learns sequential conversational context. The forward and backward DiscLSTM enable the model to integrate both the sequential and structured-discourse information from both directions in the sequence. Finally, we concatenate the hidden state $h_{t-1}$ and hidden state $h_t$ from the forward and backward states respectively to get the final hidden state representation of $t$th utterance $h_t = [h_{t-1}; \hat{h}_t]$. This final hidden state representation $H = \{h_1, h_2, h_3, \ldots, h_n\}$ is then fed to a fully-connected layer which outputs a vector representation $p_t$, $\in \mathbb{R}^d$ for each utterance $e_t$ where $d$ equals to the number of emotion classes in the ERC dataset.

### 4. Experiments

#### 4.1. Datasets and Experimental Setup

We evaluate DiscLSTM on four benchmark ERC datasets, namely IEMOCAP\(^\text{[4]}\), MELD (Multimodal EmotionLines Dataset)\(^\text{[2]}\), DailyDialog\(^\text{[17]}\), and EmoryNLP\(^\text{[18]}\). While IEMOCAP comes from scripted dyadic conversations, acted by professional actors, MELD and EmoryNLP are both obtained from specific scenes from Friends TV series. DailyDialog on the other hand is a high-quality multi-turn open-domain English dialog dataset and is less noisy than the other 3 because the conversation is human-written. All 4 datasets, IEMOCAP (happy, neutral, angry, sad, excited), MELD (anger, disgust, sadness, joy, neutral, surprise, fear), DailyDialog (emotion, anger, disgust, fear, happiness), and EmoryNLP (sad, mad, scared, powerful, peaceful, joyful, neutral) and differ in their emotion annotations. Additionally, IEMOCAP and MELD are the multimodal ERC datasets with textual, acoustic, and visual cues of each utterance available, whereas EmoryNLP and DailyDialog are unimodal with just text available. More statistics for all the datasets are shown in Table 1.

| Dataset   | Conversations Table | Utterances Train | Test          |
|-----------|---------------------|-----------------|---------------|
| IEMOCAP   | 100                  | 6490            | 2196          |
| MELD      | 11118               | 9989            | 2610          |
| DailyDialog | 11118              | 81710           | 7740          |
| EmoryNLP  | 713                  | 9934            | 1328          |

We use PyTorch deep learning framework to build, train and evaluate all our models. We use the pre-trained RoBERTa\text{large} from the Huggingface library. For training and evaluation, we use a batch size of 16 and train our networks for 100 epochs using AdaBound optimizer. We use the initial learning rate of $1e^{-3}$ with a weight decay of $1e^{-2}$. Our experimental setup is kept constant for all 4 ERC datasets.

#### 4.2. Results

Table 2 shows the effectiveness of our approach on 4 benchmark ERC datasets. We only compare with work closest to ours, which either use graph-based or recurrence-based approaches for ERC without using any external knowledge. As clearly visible, our approach performs better than all others on IEMOCAP and EmoryNLP and is competitive to the best model on MELD and DailyDialog. Additionally, as mentioned earlier, our approach is much more efficient than other approaches in literature by using just a single LSTM cell and a conversation graph that is highly sparse compared to prior-art.

| Model    | IEMOCAP | MELD | DailyDialog | EmoryNLP |
|----------|---------|------|-------------|----------|
| DialogRNN\(^\text{[9]}\) | 64.76   | 63.61 | 57.32       | 37.44    |
| KET\(^\text{[33]}\) | 63.05   | 64.28 | 56.16       | 37.10    |
| DialogueXL\(^\text{[17]}\) | 65.94   | 62.41 | 54.93       | 34.73    |
| COSMIC\(^\text{[21]}\) | 66.36   | 62.80 | 59.02       | 37.89    |
| RGAT\(^\text{[12]}\) | 66.36   | 63.12 | 58.36       | 37.89    |
| DAG-ERC\(^\text{[14]}\) | 68.03   | 63.65 | 59.33       | 39.02    |
| Baseline | 63.38   | 62.88 | 58.08       | 37.78    |
| Ours     | 68.34   | 63.75 | 59.03       | 39.11    |

### 5. Conclusions

In this paper, we propose a novel way to integrate sequential and conversational discourse context in a conversation for ERC. In addition to being simple and intuitive, our approach is competitive to the state-of-the-art on 4 ERC benchmarks using the least number of edge connections as compared to other graph approaches or without the use of any external knowledge. As part of future work, we would like to explore encoding multimodal information into our setup and push the state-of-the-art in ERC.
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