M-MELD: A MULTILINGUAL MULTI-PARTY DATASET FOR EMOTION RECOGNITION IN CONVERSATIONS

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ABSTRACT

Expression of emotions is a crucial part of daily human communication. 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. Though a lot of work has been done on ERC in the past, these works only focus on ERC in the English language, thereby ignoring any other languages. In this paper, we present Multilingual MELD (M-MELD), where we extend the Multimodal EmotionLines Dataset (MELD) [1] to 4 other languages beyond English, namely Greek, Polish, French, and Spanish. Beyond just establishing strong baselines for all of these 4 languages, we also propose a novel architecture, DiscLSTM, that uses both sequential and conversational discourse context in a conversational dialogue for ERC. Our proposed approach is computationally efficient, can transfer across languages using just a cross-lingual encoder, and achieves better performance than most uni-modal text approaches in the literature on both MELD and M-MELD. We make our data and code publicly on GitHub [1].

Index Terms— emotion recognition, multilingual, discourse learning, graph learning

1. INTRODUCTION

In the past few years, ERC has become increasingly popular as an emerging research topic in Natural Language Processing (NLP), with potential applications in areas of empathetic dialog systems [2], improved human-computer interaction [3], and social media opinion mining [4]. Researchers have proposed several methodologies [5] [6] [7] to solve this task and have primarily evaluated their systems on 4 popular benchmark datasets, namely MELD [8], IEMOCAP [9], DailyDialog [10], and EmoryNLP [11]. ERC, particularly emotion recognition in multiparty conversation (ERMC), is more challenging than tasks like sentiment classification due to the presence of emotional dynamics in conversations [8].

Though a lot of datasets and systems have been proposed for ERC, these datasets are in English, thereby ignoring any other languages. Different languages function in different ways. Building uni-modal text ERC systems for languages beyond English is especially challenging owing to the fact that recent literature shows how multi-modal cues [12] and external knowledge [7] [13] is important for ERC. Multimodal systems, though outperform text-only systems, may not be applicable in all real-world scenarios like chatbots, where only textual information is available. For text-only ERC, external cues like commonsense [13] or psychological knowledge [7] depend on external sources of knowledge like knowledge graphs, which restricts their use to ERC models trained on English due to the lack of these sources in any other language.

Main Contributions: In this paper we attempt to bridge this gap between English and non-English languages for ERC by first proposing a new dataset, M-MELD. M-MELD consists of over 4504 human-annotated text dialogues and 45871 individual utterances in 4 different languages, namely Greek, Polish, French, and Spanish, spanning 7 distinct emotions and balanced equally across 2 high-resource (French and Spanish) and 2 low-resource (Greek and Polish) languages. We describe the annotation procedure in Section 3, where we also describe why in-context human-translated dialogues are required for training better ERC systems and training over machine translated (MT) dialogues results in worse performance. Second, we also present a new model for ERC namely DiscLSTM, or Discourse-aware LSTM, which incorporates discourse-aware structured graph information into sequential recurrence-based learning. Precisely, we first train a discourse parsing model using cross-lingual embeddings from XLM-RoBERTa [14] on a popular human-annotated dataset annotated for discourse relations between human utterances [15]. Next, we infer discourse relations for dialogues in multiple languages and use these cues to incorporate a long-distance conversational background in DiscLSTM. More information on DiscLSTM can be found in Section 4. To sum up, our main contributions are as follows:

• We propose M-MELD, the first dataset for ERC in lan-
languages beyond English. M-MELD has over 45871 utterances in 4504 dialogues with human-translated utterances for ERC and is balanced across languages. Our proposed dataset is also useful in multilingual sentiment classification and as a human-annotated parallel corpus for learning MT systems. Additionally, we establish strong baselines for ERC with M-MELD.

- We propose DiscLSTM, a simple yet powerful model for ERC. Unlike most state-of-the-art systems in the literature, DiscLSTM can be easily adapted across languages and does not require external knowledge, is more resource friendly, and outperforms our text-based uni-modal baselines taken from literature.

## 2. RELATED WORK

One of the first works in this space was DialogRNN [6], which proposed modeling dialog dynamics with stacked RNNs. Following DialogRNN, the same authors proposed DialogueGCN [5], which treats each dialogue as a graph, with vertices as individual utterances, and edges connecting a vertex with its past and future turns. DAG-ERC [16] uses a Directed Acyclic Graph, which combines the benefits of graph and recurrence models with its structural properties. Very recently, MMGCN [12] proposed fusing information from multiple modalities by the use of spectral domain GCN to encode the multimodal contextual information. The work closest to DiscLSTM is [17], 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. Another popular system is DialogXL which uses dialog-aware self-attention. Finally, CoMPM [18] combines context embedding and pre-trained speaker memory to reflect the dialogue context and EmotionFlow [19] learns user-specific features to model the spread impact of emotion in a conversation.

## 3. MULTILINGUAL MELD (M-MELD)

In this section, we describe in detail the annotation procedure for M-MELD. MELD is a dataset for ERMC. In addition to the text transcript of the utterance, MELD also consists of acoustic and visual cues for each utterance. MELD has more than 1400 dialogues and 13000 utterances from the TV series Friends. Each utterance in dialogue has been labeled one of these seven emotions: Anger, Disgust, Sadness, Joy, Neutral, Surprise, and Fear. In this paper, and for M-MELD, we are only concerned with the text modality for each utterance.

DiscLSTM is a simple yet powerful model for ERC. Unlike most state-of-the-art systems in the literature, DiscLSTM can be easily adapted across languages and does not require external knowledge, is more resource friendly, and outperforms our text-based uni-modal baselines taken from literature.

### 4. DISCOURSE-AWARE LSTM

#### 4.1. Problem Formulation

The general problem of ERC can be formulated as follows. Suppose there are $m$ participants $\{p_1, p_2, p_3, \cdots, p_m\}$ in a conversation or dialogue with $n$ number of utterances $\{e_1, \cdots, e_i, \cdots, e_n\}$, where utterance $e_i$ is uttered by $p(e_i)$, and $p(\cdot)$ denotes the mapping between an utterance and its speaker. The primary objective of ERC is to predict the emotion label $y_i$ for utterance $e_i$ based on the context of the dialogue to which $e_i$ belongs. We denote a dialogue as $U_j$, where utterance $e_i \in U_j$ and $D = \{U_1, \cdots, U_j, \cdots, U_T\}$, where dataset $D$ has a total of $T$ dialogues.

#### 4.2. 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 line with prior methods [5] [16], we use the XLM-RoBERTa\textit{large} transformer model, fine-tuned on the task-specific ERC dataset to extract sentence-level features $u_i \in \mathbb{R}^{1024}$ for

| Table 1. Dataset Statistics for M-MELD |
|----------------------------------------|
| Language | # Dialogues | # Utterances |
|----------|-------------|--------------|
| French   | 633         | 6537         |
| Greek    | 870         | 9003         |
| Spanish  | 769         | 7890         |
| Polish   | 858         | 8928         |
| Total    | Train       | Dev          | Test         |
|          | 964         | 103          | 111          |
|          | 964         | 966          | 111          |
|          | 2198        | 870          | 989          |
each individual utterance \( c_i \) in the dialogue. More precisely, similar to [5], we add a \([CLS]\) token at the beginning of each tokenized utterance we feed into our XLM-RoBERTa\(_{large}\) model; the output embedding of the \([CLS]\) acts as our pooled utterance representation. Conversation \( U_j \) can now be denoted by \( U_j = \{ u_1, \cdots, u_i, \cdots, u_n \} \) or a set of utterance representations from XLM-RoBERTa\(_{large}\).

4.3. Dialogue Discourse Parsing

For dialogue discourse parsing, we first train a state-of-the-art model [20] on a human-annotated multi-party dialogue corpus STAC [15]. We view each utterance as an EDU (Elementary Discourse Unit) and use the discourse relation types defined in STAC. [20] employs a transformer backbone. One simple trick that enables us to obtain discourse relations in dialogues across languages is using cross-lingual embeddings from XLM-RoBERTa to train our discourse parsing model. Thus, even though STAC is in English, the model supports a wide range of languages during inference time.

4.4. Disc-LSTM Architecture

4.4.1. Conversation Graph Construction

With discourse relations obtained from the previous step, we construct a discourse graph \( G = (V, E) \) for each conversation, where \( V = \{ v_1, v_2, v_3, \cdots, v_n \} \) are the vertices or nodal representations of the utterances \( \{ u_1, u_2, u_3, \cdots, u_n \} \) and \( E \in \mathbb{R}^{2 \times n} \) is the adjacency matrix denoting edge relation, where \( E[i][j] = 1 \) if there is a discourse relation between utterances \( i \) and \( j \).

4.4.2. Temporal Information Flow in Graph Layers

To encode discourse relations in a conversation, we use a Graph Attention Network (GAT) [21] with the information flow through layers inspired by [22]. To feed our contextualized RoBERTa-based utterance embedding \( u_i \in \mathbb{R}^{1024} \) to our graph network, we first down-project \( e_i \) to \( g^1_i \), where a \( g^1_i \in \mathbb{R}^{100} \) via a full-connected layer \( f(.) \) as follows: \( G^1 = f(U) = \{ g^1_1, g^1_2, g^1_3, \cdots, g^1_n \} \), where \( G^1 \) is the graph-encoded representation of our utterance output by the first layer in the graph. 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:

\[
\alpha_{ij}^l = \text{softmax}_{j \in N_i}(W_{\alpha} \{ g^l_j \| g^l_i \})
\]

where \( W_{\alpha} \) are the learnable parameters and \( \| \) represents a concatenation operation. We finally gather or accumulate the information using the weights calculated above and get the subsequent layer information by: \( g^l_i = \sum_{j \in N_i} \alpha_{ij}^l g^l_j + g^{l-1}_i \).

We use the final graph layer embedding after multiple information propagation steps in the graph network and obtain \( G^l = \{ g^1_l, g^2_l, g^3_l, \cdots, g^n_l \} \) and the contextualized embeddings from the RoBERTa for our next step.

4.4.3. Bi-Directional DiscLSTM Cell

In order to better integrate both the sequential and discourse context and to dynamically learn the relative importance of each graph-encoded utterance representation for modeling a conversation, we propose DiscLSTM. DiscLSTM builds on the basic LSTM cell 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. 1. The following represents the propagation of information inside the DiscLSTM cell:

\[
\begin{align*}
\mathbf{f}_t &= \sigma \left( W_{(f)} \mathbf{u}_t + U_{(f)} \mathbf{h}_{t-1} + Q_{(f)} \mathbf{g}_t + \mathbf{b}_{(f)} \right) \\
\mathbf{o}_t &= \sigma \left( W_{(o)} \mathbf{u}_t + U_{(o)} \mathbf{h}_{t-1} + Q_{(o)} \mathbf{g}_t + \mathbf{b}_{(o)} \right) \\
\end{align*}
\]
\[
\begin{align*}
    i_t &= \sigma \left( W_{(i)} u_t + U_{(i)} h_{t-1} + b_{(i)} \right) \\
    p_t &= \sigma \left( W_{(p)} u_t + Q_{(p)} g_t + b_{(p)} \right) \\
    \tilde{c}_t &= \tanh \left( W_{(u)} u_t + U_{(u)} h_{t-1} + b_{(u)} \right) \\
    \tilde{s}_t &= \tanh \left( W_{(s)} u_t + Q_{(s)} g_t + b_{(s)} \right) \\
    c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t + p_t \odot \tilde{s}_t \\
    h_t &= o_t \odot \tanh \left( c_t \right)
\end{align*}
\]

where \( u_t \) (\( u_t \) w.r.t utterance in a dialogue) is the XLM-RoBERTa utterance representation and \( g_t \) (\( g_t \) w.r.t. utterance in a dialogue) is the graph-encoded utterance representation for the \( t \)-th time-step in the sequential processing by the bi-directional DiscLSTM cell. 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 \( h_{ij} \) and hidden state \( h_{ti} \) from the forward and backward states respectively to get the final hidden state representation of \( i \)-th utterance \( h_i = [h_{ij}; h_{ti}] \). This final hidden state representation \( H = \{ h_1, h_2, h_3, \cdots, h_n \} \) is then fed to a fully-connected layer which outputs a vector representation \( p_i \in \mathbb{R}^d \) for each utterance \( e_i \) where \( d \) equals the number of emotion classes in the ERC dataset.

5. EXPERIMENTS

Baselines: For evaluating systems from prior-art across languages in M-MELD and also to compare DiscLSTM, we choose systems that do not require an external source of knowledge, e.g., knowledge graphs, and can be easily re-implemented across languages. To the best of our knowledge, external sources of knowledge commonly used in recent literature attributing to their success \cite{12, 13} are not readily available in foreign languages beyond English. Adding to this, systems like DialogXL depend on large-scale language-specific pre-trained models and their foreign language counterparts are neither available nor resource-friendly to pre-train from scratch. On the other hand, systems like MMGCN \cite{12} leverage multiple modalities, which is not always available in a real-world setting.

Our first baseline is an XLM-RoBERTa transformer trained on a sequence classification task for ER. We adopted DialogueRNN, DialogueGCN and DAG-ERC described in Section 2 to work with utterance-level features extracted using the methodology in Section 4.2. Additionally, we fine-tune EmotionFlow and CoMPM end-to-end with XLM-RoBERTa backbone for each language. To prove the need for human-translated annotations, we also evaluate performance of all our baselines on synthetic MT data.

Experimental Setup: We use the pre-trained XLM-RoBERTa from the Huggingface library. For training and evaluation of all our systems, including baselines and DiscLSTM, we use a batch size of 16 and train our networks for 50 epochs using Adam optimizer with a learning rate of \( 1e^{-5} \). For training XLM-RoBERTa \(_{large} \) we find an optimal learning rate of \( 1e^{-4} \). Optimal hyperparameters for all other baselines were obtained from their respective papers.

6. RESULTS

Following much of prior-art, we evaluate the performance of all our baselines and our proposed DiscLSTM on the weighted \( F_1 \) score. Results are presented in Table 2. As we clearly see, DiscLSTM outperforms most of our baselines on all 4 languages in M-MELD and is close to DialogueGCN and DAS-ERC in French and Spanish. However, one must note that unlike DialogueGCN and DAG-ERC, DiscLSTM does not use future utterance information for ERC. In addition to M-MELD, we also repeat our baselines for the original MELD and the results are 62.10 / 63.16 / 63.5 / 52.81 / 50.84 / 63.75 respectively in same order as in Table 2. DiscLSTM is also more efficient than all our graph-based baselines as it uses much lesser edges on average than our other baselines which extend an edge from each utterance to all future and past utterances. Additionally, we notice a drop of 2.1% average across methods when trained on MT data. Detailed results can be found on GitHub.

| Model          | French | Spanish | Greek | Polish |
|----------------|--------|---------|-------|--------|
| XLM-RoBERTa    | 49.14  | 52.30   | 52.70 | 31.0   |
| DialogueRNN    | 50.19  | 52.50   | 53.10 | 31.41  |
| DialogueGCN    | 51.20  | 52.81   | 53.46 | 31.90  |
| CoMPM          | 35.41  | 49.00   | 42.76 | 37.03  |
| EmotionFlow    | 35.69  | 41.65   | 43.13 | 42.20  |
| DAG-ERC        | 49.10  | 52.9    | 53.40 | 42.23  |
| DiscLSTM (ours)| 49.43  | 53.24   | 53.46 | 43.21  |

7. CONCLUSION

In this paper, we present M-MELD, the first publicly available multilingual dataset for ERC in languages beyond English, namely French, Spanish, Greek, and Polish. We establish strong baselines from literature for all 4 languages in M-MELD and discuss how most modern systems achieving state-of-the-art in MELD get restricted to their usage just in English. Our dataset opens new challenges to the research community in designing ERC systems that can be easily transferred across languages. Additionally, we also propose a new and efficient system for ERC, DiscLSTM, which outperforms all our unimodal text baselines across MELD and M-MELD. A limitation of DiscLSTM is the two-step approach where error does not propagate across stages. As part of future work we would devise better end-to-end language-independent ERC systems.
8. REFERENCES

[1] Soujanya Poria, Devamanyu Hazarika, Navonil Majumder, Gautam Naik, Erik Cambria, and Rada Mihalcea, “Meld: A multimodal multi-party dataset for emotion recognition in conversations,” arXiv preprint arXiv:1810.02508, 2018.

[2] Navonil Majumder, Pengfei Hong, Shanshan Peng, Jiankun Lu, Deepanway Ghosal, Alexander Gelbukh, Rada Mihalcea, and Soujanya Poria, “Mime: Mimicking emotions for empathetic response generation,” arXiv preprint arXiv:2010.01454, 2020.

[3] Roddy Cowie, Ellen Douglas-Cowie, Nicolas Tsapatsoulis, George Votsis, Stefanos Kollias, Winfried Felzenz, and John G Taylor, “Emotion recognition in human-computer interaction,” IEEE Signal processing magazine, vol. 18, no. 1, pp. 32–80, 2001.

[4] Ankush Chatterjee, Kedhar Nath Narahari, Meghana Joshi, and Puneet Agrawal, “Semeval-2019 task 3: Emocontext contextual emotion detection in text,” in SemEval 2019, pp. 39–48.

[5] Deepanway Ghosal, Navonil Majumder, Soujanya Poria, Niyati Chhaya, and Alexander Gelbukh, “DialogueGCN: A graph convolutional neural network for emotion recognition in conversation,” in EMNLP-IJCNLP 2019.

[6] Navonil Majumder, Soujanya Poria, Devamanyu Hazarika, Rada Mihalcea, Alexander Gelbukh, and Erik Cambria, “Dialoguernn: An attentive rnn for emotion detection in conversations,” in AAAI 2019, vol. 33, pp. 6818–6825.

[7] Deepanway Ghosal, Navonil Majumder, Alexander Gelbukh, Rada Mihalcea, and Soujanya Poria, “Cosmic: Commonsense knowledge for emotion identification in conversations,” arXiv preprint arXiv:2010.02795, 2020.

[8] Soujanya Poria, Devamanyu Hazarika, Navonil Majumder, Gautam Naik, Erik Cambria, and Rada Mihalcea, “MELD: A multimodal multi-party dataset for emotion recognition in conversations,” in ACL 2019, pp. 527–536.

[9] Carlos Busso, Murtaza Bulut, Chi-Chun Lee, Abe Kazemzadeh, Emily Mower, Samuel Kim, Jeannette N Chang, Sungbok Lee, and Shrikanth S Narayanan, “Iemocap: Interactive emotional dyadic motion capture database,” LREC 2018, vol. 42, pp. 335–359.

[10] Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu, “DailyDialog: A manually labelled multi-turn dialogue dataset,” in IJCNLP 2017.

[11] Sayyed M Zahiri and Jinho D Choi, “Emotion detection on tv show transcripts with sequence-based convolutional neural networks,” in AAAI Workshop 2018.

[12] Jingwen Hu, Yuchen Liu, Jinming Zhao, and Qin Jin, “MMGCN: Multimodal fusion via deep graph convolution network for emotion recognition in conversation,” in ACL-IJCNLP 2021.

[13] Jiangnan Li, Zheng Lin, Peng Fu, and Weiping Wang, “Past, present, and future: Conversational emotion recognition through structural modeling of psychological knowledge,” in EMNLP 2021, pp. 1204–1214.

[14] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov, “Unsupervised cross-lingual representation learning at scale,” arXiv preprint arXiv:1911.02116, 2019.

[15] Nicholas Asher, Julie Hunter, Mathieu Morey, Benamara Farah, and Stergos Afantenos, “Discourse structure and dialogue acts in multiparty dialogue: the STAC corpus,” in LREC 2016, pp. 2721–2727.

[16] Weizhou Shen, Siyue Wu, Yunyi Yang, and Xiaojun Quan, “Directed acyclic graph network for conversational emotion recognition,” in ACL-IJCNLP 2021.

[17] Yang Sun, Nan Yu, and Guohong Fu, “A discourse-aware graph neural network for emotion recognition in multi-party conversation,” in Findings of EMNLP 2021, pp. 2949–2958.

[18] Joosung Lee and Wooin Lee, “CoMPM: Context modeling with speaker’s pre-trained memory tracking for emotion recognition in conversation,” in NAACL:HLT 2022, pp. 5669–5679.

[19] Xiaohui Song, Liangjun Zang, Songlin Hu, and Longtao Huang, “Emotionflow: Capture the dialogue level emotion transitions,” in IEEE ICASSP 2022, pp. 8542–8546.

[20] Zhengyuan Liu and Nancy F Chen, “Improving multi-party dialogue discourse parsing via domain integration,” arXiv preprint arXiv:2110.04526, 2021.

[21] Petar Veličković, Guilleum Cucurull, Arantxa Casanova, Adriana Romero, Pietro Lio, and Yoshua Bengio, “Graph attention networks,” arXiv preprint arXiv:1710.10903, 2017.

[22] Weizhou Shen, Siyue Wu, Yunyi Yang, and Xiaojun Quan, “Directed acyclic graph network for conversational emotion recognition,” in ACL-IJCNLP 2021, pp. 1551–1560.