Transferring Knowledge Distillation for Multilingual Social Event Detection

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Abstract—Recently published graph neural networks (GNNs) show promising performance at social event detection tasks. However, most studies are oriented toward monolingual data in languages with abundant training samples. This has left the more common multilingual settings and lesser-spoken languages relatively unexplored. Thus, we present a GNN that incorporates cross-lingual word embeddings for detecting events in multilingual data streams. The first exploit is to make the GNN work with multilingual data. For this, we outline a construction strategy that aligns messages in different languages at both the node and semantic levels. Relationships between messages are established by merging entities that are the same but are referred to in different languages. Non-English message representations are converted into English semantic space via the cross-lingual word embeddings. The resulting message graph is then uniformly encoded by a GNN model. In special cases where a lesser-spoken language needs to be detected, a novel cross-lingual knowledge distillation framework, called CLKD, exploits prior knowledge learned from similar threads in English to make up for the paucity of annotated data. Experiments on both synthetic and real-world datasets show the framework to be highly effective at detection in both multilingual data and in languages where training samples are scarce.

Index Terms—Social Event Detection, Graph Neural Networks, Knowledge Distillation, Cross-lingual Word Embeddings

1 INTRODUCTION
The task of social event detection means to extract information about important and often newsworthy, real-world occurrences from social media data streams [1]. When event detection first comes to the fore, most studies on the subject treat event detection as either an incremental clustering problem [1], [2], [3], [4], a community detection problem [5], [6], [7], [8], [9], or a topic modeling problem [10], [11], [12], [13], [14]. However, in using these approaches, scholars are ignoring much of the rich semantics and structural information social streams contain. Hence, more recently, researchers have turned to the expressive power of graph neural networks (GNNs) [15], [16] – both homogeneous and heterogeneous – to capture this information [17], [18], [19]. Among these new approaches, one called KPGNN [19] has

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Fig. 1: An illustration of multilingual social graph construction strategy. (a) shows three monolingual heterogeneous information graphs corresponding to English, French and Arabic data respectively. Each graph consists of four types of nodes: users, hashtags, entities and messages. With all kinds of valuable elements preserved in the graph, the knowledge contained in the social stream can be greatly explored. (b) is the unified multilingual heterogeneous information graph combined by the three graphs in (a) based on the two-level alignment including node-level alignment and semantic-level alignment. (c) is the multilingual homogeneous message graph transformed from (b). Specifically, if two messages link to the same user, or hashtag, or entity, these two message nodes are connected.
constructed message graph \( G(\mathbf{A}_t, \mathbf{X}_t) \) of student-language data and \( G(\mathbf{A}_s, \mathbf{X}_s) \) of teacher-language data, as well as the transformed message graph \( G(\mathbf{A}_s, \mathbf{X}_s, \mathbf{m}_t) \) of student-language data in teacher’s semantic space.

**Fig. 2:** An illustration of the cross-lingual knowledge distillation framework. We utilize the priors learned from the model pre-trained on teacher language data to segment the student model trained on student language data by making their predicted distributions similar.

We successfully addressed the incremental detection of events in Twitter data from a knowledge-preserving perspective. This is tremendous progress, but there are still questions to be answered. For instance, in general, GNN-based detection is oriented toward monolingual data where there are ample instances for training (i.e., high-resource languages), and particularly English. But can these GNN solutions work in multilingual situations? And what can we do for languages where training samples are scarce? As more of the world becomes connected, people are increasingly using different languages on social media to share their opinions of the same event. Further, more and more social media platforms are offering dedicated sites in alternative languages. Thus, there are two valuable research topics to explore in multilingual social event detection. One is to design a framework that can overcome language barriers so as to uniformly handle data consisting of multiple languages (see Fig. 1). The other is to strengthen detection capabilities in low-resource languages using knowledge learned from high-resource languages (see Fig. 2). Unfortunately, very few studies focus on these two scenarios; hence, fulfilling these two challenges is our research goal.

In recent years, multilingual models such as M-BERT from BERT [20] and XLM-R [21] have gained increasing popularity among the NLP community. However, the full extent to which they can be generalized is questionable. In practice, they perform better with linguistically similar languages. For this reason, we opt to leverage CLWE to achieve our goals. This is also motivated by the success of cross-lingual word embeddings (CLWE) in tasks like multilingual offensive language identification [22]. Rather than learning a joint vector space for all languages, CLWE learns on monolingual data, first learning the specific vector space for each language and then mapping them together. Hence, a non-English vector space can be independently transformed into English. To the best of our knowledge, CLWE has not yet been applied to social event detection tasks. Additionally, as shown with PP-GCN [17] and KP-GNN [19], when a GNN’s parameters are tuned for event detection, such models can capture much of the knowledge locked within social data.

Our implementation involves a multi-head GAT [23] model as the learning backbone but relies on a new graph construction strategy to make the GNN encoder compatible with multilingual data. The graph construction process is demonstrated in Fig. 1. Multilingual data is processed by a heterogeneous information network that consists of four types of nodes – users, entities, hashtags, and messages. The key problem that needs to be solved is the alignment of messages in different languages, so here is where the novel construction strategy come in. Incorporating both node-level alignment and semantic-level alignment, the entity nodes are aligned with XLEnt [24]. We choose XLEnt as a tool because it comprises parallel entities in 120 languages aligned to English. The semantics are aligned with CLWE methods to break the embedding space discrepancy among different languages. Through a cross-lingual module that uses CLWE methods, we transform those non-English languages’ embedding spaces to English semantic space. Note that the cross-lingual module considers both linear [25] and non-linear [26] CLWE mapping methods with the method that gives the most appropriate transformation between language pairs selected as the final result.

Turning to the low-resource language problem, in the past, a variety of approaches have been suggested for handling scenarios with a lack of sufficient training samples, including transfer learning and meta learning. Another promising approach is cross-modal knowledge distillation [27], which uses priors from a model trained with superior modality (the teacher) to segment another model trained with a weak modality (the student) by making their predicted distributions similar. Usually, the superior modality should have an adequate amount of high-quality data while the student modalities only have access to small or poor-quality datasets. Despite their tremendous variations and diversity, languages do share some things in common. For us, the superior “teacher” modality is English, while the weak “student” modality is the low-resource language – in our experiments, these are Arabic and French. Hence, we propose a cross-lingual knowledge distillation (CLKD) framework that leverages the prior knowledge learned from a high-resource language (i.e. English) to make up for a lack of annotated samples in the low-resource languages (i.e. Arabic and French).

Our proposed CLKD framework adopts different structures to suit both offline and online situations. As shown in Fig. 3 (a), this is an offline solution that combines CLWE with knowledge distillation and follows a Teacher-Student structure – offline because traditional Teacher-Student knowledge distillation requires a two-stage training strategy that does not suit online situations. To alleviate the difficulties caused by language discrepancy, before input student language samples to the pre-trained teacher model, we leverage the cross-lingual module. The framework also incorporates a mutual learning structure which follows a one-stage learning strategy so that this framework can be...
applied to detect events in incremental settings. As shown in Fig. 3(b), the online mutual distillation thoroughly exploits language-shared knowledge through mutual instruction between two GNN peers to facilitate network learning. The cross-lingual module similarly works in both directions.

To test the multilingual GNN detection framework, we prepare a human-generated multilingual dataset consisting of English, French, and Arabic. To evaluate the CLKD framework for low-resource transfer scenarios, we use three publicly-available datasets of Twitter data – English [28], French [29], and Arabic [30]. The results show our multilingual GNN detection framework successfully detect events from data streams containing three languages. For the low-resource scenarios, using CLKD and relying on prior knowledge from English substantially improve detection in French and Arabic. The main contributions of this paper therefore include:

1) A novel strategy for constructing graphs from multilingual social data. The approach mainly involves aligning the data at two levels – node and semantic – to make standard GNN techniques compatible with multilingual social event detection tasks. At the node level, entity alignment is used to construct a unified graph consisting of multilingual data. At the semantic level, CLWE methods convert all non-English message representations into English semantic space.

2) A novel cross-lingual knowledge distillation (CLKD) framework. This framework is designed to detect events in a low-resource language by borrowing prior knowledge from a high-resource language.

3) A solution to multilingual social event detection tasks. Our experiments return a result of .64±.01 NMI, .53±.01 AMI and .33±.01 ARI on a dataset containing English, French, and Arabic, proving that the problem of detecting events in multilingual social media streams has been solved.

4) Experimental results on two real-world datasets – one in French and one in Arabic – demonstrating that the performance of social event detection can be greatly improved in situations of data paucity by combining a GNN model with knowledge distillation into a CLKD framework.

2 Preliminary

This section sets out the main notations used in this paper, as shown in Table 1. Then we expand the definitions of Social Stream and Social Event in [19], and give the definitions of Multilingual Social Event Detection and Cross-lingual Social Event Detection.

Definition 2.1. A social stream \( S = M_0, ..., M_{i-1}, M_i, \ldots \) is a continuous and temporal sequence of blocks of social messages which can be monolingual or multilingual. A monolingual social event \( e \) in a monolingual social stream is a set of correlated messages that discuss the same real-world happening in the same language. A multilingual social event \( e' \) in a multilingual social stream is discussed in different languages \( l \). There are \( |l| \) languages in total, where \(|l| > 1\), \( \forall i \in [1,|l|], \exists j \in [1,|e'|], \Rightarrow L(m_j) = l_i \), where \( L(m_j) \) means the corresponding language of \( m_j \). In this work, it is assumed that each message discusses at most one event.

Definition 2.2. A multilingual social event detection algorithm learns a model \( f(M_i; \theta) \), where \( \theta \) denotes the parameters in the network, and \( M_i \) denotes a message block containing a set of multilingual social event \( e' \). The multilingual social graph of \( M_i \) is constructed through entity alignment. The initial attribute features of non-English messages in \( M_i \) are transformed to English semantic space through the cross-lingual module.

Definition 2.3. For cross-lingual social event detection, priors learned from a high-resource language are used to segment the performance of a low-resource language. The message block in the high-resource language is denoted as \( M_i^h \) and as \( M_i^l \) for the low-resource language. Both \( M_i^h \) and \( M_i^l \) are monolingual. The model \( f(M_i^h; \theta^h) \) is learned through a specific social event detection algorithm. The model for the low-resource language \( M_i^l \), \( f(M_i^l; \theta^l) \), is learned through the same event detection algorithm but under the supervision of the output of \( f(M_i^h; \theta^h) \), where \( \theta^h \) is the already trained network parameters by high-resource language data, \( M_i^{\sim h} \) is the transformed low-resource language data in high-resource language semantic space.

3 Methodology

This section sets out our two frameworks for detecting events in social media data – one for multilingual data, the other for single low-resource languages. The description begins with the cross-lingual module in Section 3.1. Section 3.2 introduces the novel multilingual graph construction strategy which makes GNN methods applicable to multilingual data. In Section 3.3 we consider the case of low-resource languages and the dedicated cross-lingual knowledge distillation (CLKD) framework in both offline and online situations. Section 3.4 sets out the life-cycle and stages of the framework’s operation. And we conclude in Section 3.5 with a time complexity analysis.

3.1 Cross-Lingual Module

Different languages do not share a joint vector space, which means, the learned representations for the same thing ex-
pressed in different languages varies greatly. This makes social event detection in multilingual situations challenging. Also, it means sharing knowledge learned in one language with another is problematic. Our solution for overcoming these issues is to use CLWE.

The process begins by training a monolingual embedding model for each language considered. This could be done through any of the well-known word embedding algorithms (e.g., Word2Vec [31], GloVe [32], or FastText [33]). We use the pre-trained language models in spacy\footnote{https://spacy.io/api/annotation#section-named-entities}, which are trained by GloVe. After deriving all isolated monolingual vector spaces, the mappings between each non-English language and English pair are learned in both directions. To explore the most appropriate transformations, we try both linear and nonlinear CLWE methods.

The goal with the linear mapping is to learn a matrix $W$ between the source and the target space such that $W = \text{argmin} \| W \cdot X - Y \|$, where $X$ and $Y$ denote the embeddings for the source words and the target words respectively. This linear approach follows the assumption that the source and target embedding spaces are approximately isomorphic, and will likely suit languages that follow similar grammatical and vocabulary structures. We choose MUSE\cite{25} to learn the linear mapping between all language pairs as it has yielded great results in aligning two monolingual embedding spaces. The cross-lingual word embeddings are created by a Generative Adversarial Networks (GANs), where the generator learns the transformation matrix $W_i$, ensuring that the transformed non-English embeddings $W \cdot X$ approximate the English semantic embeddings $Y$ as closely as possible. The discriminator tries to classify whether the embeddings from the English embedding distribution are real ones or transformed. Do note, however, that MUSE is not the only choice. Other linear methods like VecMap\cite{34} would also be suitable.

For the non-linear mapping, we choose LNMAP\cite{26}. LNMAP is a model that operates independently of isomorphic assumption. It comprises two auto-encoders with non-linear hidden layers for each language. The auto-encoders are first trained independently in a self-supervised way to induce the latent code space of the respective languages. A small seed dictionary is then used to learn the non-linear mappings, which are implemented as feed-forward neural networks with non-linear activation layers between the two learned latent spaces. As the first non-linear cross-lingual word embeddings method, LNMAP has shown outstanding performance with many language pairs including far-distance language pairs.

We use the linear and nonlinear mapping learned by MUSE and LNMAP for each non-English-English pair to build the cross-lingual language models in both directions.

### 3.2 Multilingual Social Graph Construction

The strategy for constructing multilingual social graphs is shown in Fig. 1. To capture as much information as possible from the social stream, a series of useful elements are extracted at the data processing stage and depicted in a heterogeneous information graph. Generally, four kinds of nodes are extracted – users, named entities, hashtags, and the messages themselves. As the main focus is to learn the correlations between messages, the heterogeneous social graphs are transformed into a homogeneous message graph by noting the common neighbors of the messages. For example, if two message nodes link to the same user, entity, or hashtag, a connection is formed between these two message nodes. In this way, we obtain a handled homogeneous message graph $G(X, A)$, where $A$ is the adjacency matrix and $X$ denotes the initial attribute features of the nodes, which is the average of the message’s word embeddings.

In addition to the construction steps above, two further alignment technologies are integral to establish a unified multilingual graph. The first is node-level alignment. Note that the entities extracted from multilingual social event data are in different languages, which means that there may be different representations in different languages for the same entity. This makes it difficult to capture relationships between messages in multiple languages. To overcome these inconsistencies, we turn to entity alignment technology. Specifically, we use the cross-lingual named-entity lexicons provided by Author\cite{24}. These lexicons contain over 164 million distinct cross-lingual entity pairs spanning 120 languages and, using them, the model can convert non-English entities into English. Thus, through this process, different representations of the same entity are merged together. The second integral step is semantic-level alignment. The initial representations of messages in different languages are in different embedding spaces. As with the attribute features of the French and Arabic messages, the cross-lingual language models described in Section 3.1 are used to project the representations of messages in different languages are in semantic space. Thus, messages in different languages wind up in the same space and can be encoded uniformly by a purpose-built GNN encoder. For convenience, we refer to this whole process as the multilingual GNN detection framework.

We implement a 2-layer multi-head GAT network as the GNN encoder and use a contrastive triplet loss\cite{35} for back propagation. $L_t$ denotes the loss calculated by a set of triplets $<\text{anchor}, \text{positive}, \text{negative}>$ based on true labels. The objective $L_t(h)$ is to build triplets $<h_{mi}, h_{mi+}, h_{mi-}>$ and to keep the distance between the anchor $h_{mi}$ and the positive $h_{mi+}$ smaller than the distance between the anchor $h_{mi}$ and the negative $h_{mi-}$. Here positive denotes a message whose label is as same as the anchor’s while the label of negative is different from the anchor’s.

### 3.3 Cross-Lingual Knowledge Distillation

The CLKD framework is for cases where one wishes to detect events in a low-resource language. The procedure essentially borrows knowledge learned from a high-resource language (English) and uses it to assist learning in a low-resource language. There is a large quantity of English event data that is already labeled. As shown in Fig. 3, we devise two distillation architectures – one Teacher-Student configuration, intended for offline use, and the other mutual learning configuration, designed for online situations. However, the backbone of both architectures is the same GNN encoder, which is a 2-layer multi-head GAT model.
Algorithm 1: Training procedure of CLKD framework (Teacher-student)

**Input:** The original student-language dataset \((X_s, A_s)\); The transformed student-language dataset in teacher’s semantic space \((X_{s\rightarrow t}, A_t)\); The pre-trained teacher’s network \(\theta_t\); Maximum training epoch number \(E\).

**Output:** Trained student network \(\theta^s\).

1. initialization \((e=1)\); Randomly initialize \(\theta^s\);
2. while \(e \leq E\) do
3. Compute \(h_{stu}^s\) of student network;
4. Compute \(h_{tea}^t\) of teacher network;
5. Compute the triplet loss \(L_t(h_{stu}^s)\) of student network;
6. Compute the knowledge distillation loss \(L_{KD}^{stu}\); 
7. Compute the total loss of student network \(L_{total}\);
8. Back-propagation to update student network \(\theta^s\);
9. \(e = e + 1\);
10. end

### 3.3.1 Teacher-student structure

As shown in Fig. 3 (a), the Teacher-Student structure is designed for offline situations. In our experiments, the network intended for French or Arabic event detection is regarded as the student and the network pre-trained on a large-scale English dataset is the teacher. Note that the students and teacher share the same network structure and the training procedure follows a classic two-stage process. First, we train the teacher network and fix the parameters. Then, we train the student network. Each student is not only encouraged to explicitly learn the detection knowledge from the ground-truth labels of its data, but it is also guided to explore knowledge from the output representations of the teacher. Algo. 1 provides details of the procedure. Specifically, during the training process of the student, we have the processed student-language message graph \(G(X_s, A_s)\). We also utilize the corresponding student-language \(\rightarrow\) teacher-language cross-lingual language models learned in Section 3.1 to get the transformed initial attribute features of messages \(X_s\rightarrow t\) in English semantic space. The pair \(G(X_s, A_s)\) and \(G(X_{s\rightarrow t}, A_t)\) is the input to student and teacher networks respectively. The aim to obtain cross-lingual attribute features \(X_s\rightarrow p\) is to eliminate the existing language discrepancy when French or Arabic data being input to the pre-trained teacher model specified for English. To use a real-world analogy, this process is similar to a case where there is an expert who has rich experience in social event detection but only understands English and a student, inexperienced in social event detection, speaks another small language. The messages are converted into English before shown to the expert. The expert can then use its expertise in social event detection to teach the student how to detect events by way of example. To transfer prior knowledge from the
English expert to the French and Arabic students, the final message outputs of teacher model $h^{tea}$ are used as an extra supervisory signal. The distillation loss encourages the student to mimic the teacher:

$$L_{KD}^{stu} = \min(\sum_i \text{distance}(h_{m_i}^{stu}, h_{m_i}^{tea})).$$  \hspace{1cm} (1)

Here, we define the distillation loss as minimizing the distance between the raw logits from the teacher $h^{tea}$ and the student’s final representations $h^{stu}$. The distance can be measured by different metrics such as Manhattan distance, Euclidean distance and so on. As for the back propagation of the student training network, we set the total loss as a weighted sum of the knowledge distillation loss and the triplet loss based on true labels:

$$L_{total}^{stu} = L_t(h^{stu}) + \lambda L_{KD}^{stu},$$  \hspace{1cm} (2)

where $\lambda$ is a hyper-parameter that controls the weight of the knowledge distillation loss.

### 3.3.2 Mutual-Learning Structure

Fig. 3(b) shows the mutual distillation scheme, designed for online situations. This configuration is motivated by Author [55], who contends that students can learn from each other. We have formulated the structure as a cohort of two networks that exploit knowledge from each other. Hence, both networks are strengthened through the help of their peer. The training details are shown in Algo. 2. We have two processed monolingual social event data $G(X_{p1}, A_{p1})$ and $G(X_{p2}, A_{p2})$ specified for the training of peer1 network and peer2 network respectively. Similarly, we also get the transformed peer1 data in peer2-language semantic space $G(X_{p1→p2}, A_{p1})$ and the transformed peer2 data in peer1-language semantic space $G(X_{p2→p1}, A_{p2})$ by the corresponding cross-lingual language models. To enhance learning, during the training process, explicit knowledge is not only leveraged from the true labels, implicit knowledge from the peer is also used. For example, as for the training of peer1 network, $G(X_{p1}, A_{p1})$ and $G(X_{p1→p2}, A_{p2})$ are simultaneously input into peer1 and peer2 network respectively, with the corresponding outputs of $h^{p1}$ and $h^{p1→p2}$. $h^{p1→p2}$ is used as an extra supervisory signal of peer1. The distillation loss of peer1 is:

$$L_{KD}^{p1} = \min(\sum_i \text{distance}(h_{m_i}^{p1}, h_{m_i}^{p1→p2})).$$  \hspace{1cm} (3)

Similarly, for peer2, the distillation loss is:

$$L_{KD}^{p2} = \min(\sum_i \text{distance}(h_{m_i}^{p2}, h_{m_i}^{p2→p1})).$$  \hspace{1cm} (4)

The total loss of peer1 and peer2 is formulated as the weighted combination of the corresponding triplet loss based on true labels and the corresponding knowledge distillation loss:

$$L_{total}^{p1} = L_t(h^{p1}) + \lambda L_{KD}^{p1},$$  \hspace{1cm} (5)

$$L_{total}^{p2} = L_t(h^{p2}) + \lambda L_{KD}^{p2}.$$  \hspace{1cm} (6)

The entire framework is trained in an online manner, and the weights of peer1 and peer2 are updated in an alternating manner according to the combined loss. Suppose peer1 has richer training data and the target is to get better peer2 network performance. From peer1’s view, the knowledge distillation $L_{KD}^{p1}$ provides the knowledge learned from its peer, which guides peer1 to implicitly generalize towards a more reliable direction to help detect peer2 data. In other words, with the knowledge distilled from peer2, peer1 provides better suggestions to help peer2 extract events from its data. From peer2’s view, the knowledge distillation loss $L_{KD}^{p2}$ brings additional knowledge from peer1 that serves to augment and directly enhance peer2’s generalization ability. Further, an ensemble strategy is used to explore more informative and comprehensive cross-lingual knowledge in the final detection of the target peer2’s data. In detail, to do the final message clustering, peer1’s final representations $h^{p2→p1}$ of the transformed peer2 data $G(X_{p2→p1}, A_{p2})$ are concatenated with peer2’s final representations $h^{p2}$ of the peer2 data $G(X_{p2}, A_{p2})$. This process is similar to a case with two student peers – one speaks English and the other does not. The student who speaks another language learns the message representations in her own language but also uses knowledge gained from any messages learned by her English-speaking peer. The opinions of both students are then combined to make a more general and informed decisions.

### Algorithm 2

**Input:** The original peer1-language dataset $(X_{p1}, A_{p1})$; The transformed peer1-language dataset in peer2’s semantic space $(X_{p1→p2}, A_{p1})$; The original peer2-language dataset $(X_{p2}, A_{p2})$; The transformed peer2-language dataset in peer1’s semantic space $(X_{p2→p1}, A_{p2})$; Maximum training epoch number $E$.

**Output:** Trained peer1 network $\theta^{p1}$ and peer2 network $\theta^{p2}$.

1. **Initialization** ($e=1$; Randomly initialize $\theta^{p1}$ and $\theta^{p2}$);
2. **while** $e \leq E$ **do**
   3. Compute $h^{p1}$ of peer1, $h^{p1→p2}$ of peer2;
   4. Compute $h^{p2}$ of peer2, $h^{p2→p1}$ of peer1;
   5. Compute the triplet loss $L_t(h^{p1})$ of peer1, $L_t(h^{p2})$ of peer2;
   6. Compute the knowledge distillation loss $L_{KD}^{p1}$ of peer1, $L_{KD}^{p2}$ of peer2;
   7. Compute the total loss $L_{total}^{p1}$ of peer1, $L_{total}^{p2}$ of peer2;
   8. **Back-propagation** to update peer1 network $\theta^{p1}$ and peer2 network $\theta^{p2}$;
   9. $e = e + 1$;
10. **end**

### 3.4 Continuous Detection Framework

To extend the framework adapt to online (incremental) scenarios, we follow a life-cycle that contains three stages: pre-training, detection, and maintenance. In the pre-training stage, an initial message graph is constructed from the first
few message blocks and an initial model is trained. The pre-training stage only runs once. In the detection stage, a new graph is constructed for each coming block. We directly detect events of each coming block with the already trained model. In the maintenance stage, we continuously train the model with the newest message block, allowing the model to learn new knowledge. These two phases alternate. In this way, the model continuously adapts to incoming data. It can detect new events and update the model’s knowledge. It also ensures a light training scheme as obsolete nodes in past blocks are deleted.

4 Experiments

To evaluate our two solutions, we conduct online and offline experiments with both real and synthetic datasets. To test the multilingual GNN detection framework, we assemble a multilingual dataset consisting of English, French, and Arabic. To test the CLKD framework, we use three publicly-available datasets containing Twitter messages – one each in English, French, and Arabic. The backbone of both frameworks is the GNN encoder. As described in the Methodology, this is configured as a two-layer multi-head GAT model, i.e., KPGNN as reported in [19].

4.1 Experimental Setup

4.1.1 Datasets

Of the four datasets, the multilingual dataset is assembled from 20,000 tweets filtered out of the first week of the English Twitter dataset described below. From these 20,000, we select 5000 tweets and translate them into French and a further 5000 and translate them into Arabic both using the Google Translate API. The final multilingual dataset consists of 20,000 tweets, spanning 155 event classes. The three Twitter datasets are filtered for duplicate and unavailable tweets, leaving the following record counts:

- **English Twitter dataset** [28] – 68,841 manually-labeled tweets relating to 503 event classes, spreads over a period of 29 days.
- **French Twitter dataset** [29] – 64,516 labeled tweets relating to 257 event classes over 23 days.
- **Arabic Twitter dataset** [30] – 9,070 labeled tweets relating to 7 crisis-class events over different periods.

To evaluate the CLKD framework, in the offline tests, the teacher is trained on the English Twitter dataset, and the students are trained on the French and Arabic Twitter datasets. The goal of the task is to detect events in the French and Arabic stream. In the online tests, we use the English and French datasets in a mutual learning scheme comprising two peer networks. The goal of the task is to detect events in the French stream.

Fig. 4 shows how the four datasets are partitioned between all the events. Obviously, the numbers of messages are very unbalanced, making the detection task more difficult by design.

3.5 Time Complexity Analysis

The overall running time (except the CLKD framework in Mutual-Learning structure) is $O(N_e)$, where $N_e$ is the total number of edges in the message graph. In detail, the running time for constructing a monolingual message graph is $O(N + N_e) = O(N_e)$, where $N$ is the total number of messages in the message graph. Since the cross-lingual language models (mentioned in Section 3.1) can be pre-computed before training. As for multilingual social graph construction, the extra process needed is entity alignment based on lexicons (mentioned in Section 3.2) and semantic space alignment based on the cross-lingual module whose running time is $O(N)$. In terms of the Teacher-Student CLKD framework, (teacher is pre-trained and fixed), we need $O(N)$ to obtain English semantic features. Propagating the GNN encoder takes $O(N d'd + N_e d') = O(N_e)$, where $d$ and $d'$ are the input and output dimensions of the GNN encoder. For the loss calculation, triplet sampling takes $O(\sum_{b=1}^{B} |m_b|^2)$, where $|m_b|$ is the number of messages in the $b$-th batch and $B$ is the total number of batches. Plus, another $O(\sum_{b=1}^{B} |m_b|^2)$ is required to calculate knowledge distillation loss. In reality, $O(\sum_{b=1}^{B} |m_b|^2) \ll N_e$. Thus, the total complexity is $O(N_e)$.

We then analyze the overall running time of the CLKD framework in mutual learning structure. Suppose the total number of edges and nodes of the auxiliary data we select are $N'_e$ and $N'_v$, if $N'_e$ is in the same order of magnitude with $N_e$, the overall running time is $O(N_e)$. If $N'_e \gg N_e$, the overall running time is $O(N'_e)$. Since the time of mutual learning can be seen as the sum of the run-time of the auxiliary data and of the target data in the Teacher-Student structure.

Fig. 4: Dataset statistics. (a), (b), (c), (d) show the number of messages related to each event on the English dataset, French dataset, Arabic dataset and the multilingual dataset respectively.
4.1.2 Baselines

Most models in the social event detection domain are designed for monolingual data, including general message representation learning, offline social event detection methods, and incremental ones. We select the following methods as baselines of the CLKD framework: Word2Vec [31], which uses the average of the pre-trained Word2Vec embeddings of all words in the message as its representation; BERT [20], which uses the averaging BERT embeddings of all the words in a message as its representation; LDA [37], which is the most typical topic model in NLP to cluster texts; Pairwise Popularity Graph Convolutional Network (PP-GCN) [17], which is an offline fine-grained social event detection method based on GCN [38]; EventX [6], which is a fine-grained event detection method based on community detection, applicable to online scenarios; KPGNN [19], which leverages the inductive learning ability of GNNs to efficiently detect events and extends knowledge to the previously unseen data. KPGNN has shown promising performance in social event detection tasks for both offline and online situations.

As for multilingual event detection tasks, there are no effective baselines. In experiments, we use the results obtained by KPGNN in the three monolingual parts as comparisons to the multilingual GNN detection framework in the whole multilingual dataset. To further measure the performance of the cross-lingual module, we also combine the popular multilingual model M-BERT from BERT [20] with KPGNN as a baseline, named KPGNN+M-BERT. For KPGNN+M-BERT, we utilize the averaging M-BERT embeddings of all the words in a message as its representation and then update all message nodes through KPGNN.

4.1.3 Experimental Setting and Implementation

For Word2Vec, we use the pre-trained 300-d language model [31]. For LDA, we set the topic number 50. For BERT, we use the open-source implementation [4] and adopt an average 768-d hidden-states of tokens in the last layer as the embeddings. For EventX, we follow the hyper-parameters settings suggested in the original paper. For the GNN-based methods (PP-GCN, KPGNN) which we select as baselines and the backbone of this work, we follow the hyper-parameters settings in KPGNN paper [19]. Specifically, we set the total number of heads $h$ to 4, the hidden embedding dimension and output dimension $d$ to 32, the total number of layers $L$ to 2, learning rate to 0.001, optimizer to Adam, and training epochs to 15 with a patience of 5 for early stopping. Meanwhile, for the CLKD framework, we choose Manhattan-distance for the distance metric in knowledge distillation. The weight of the knowledge distillation loss $\lambda$ is set to 1 in Teacher-Student structure, and to 0.1 in Mutual-Learning structure. The mini-batch size $|\{m_b\}|$ is 2000 and the maintenance window size $w$ is 3, which means the network is retrained every 3 message blocks. We repeat all experiments for 5 times and report the mean and standard variance of the results. Note that some baselines (Word2Vec, LDA) require the number of total event classes to be predefined. For a fair comparison, we apply K-means clustering after obtaining the message representations from the other models and set the total number of classes to the number of ground-truth classes. Outside an experimental setting, DBSCAN could be used if the total number of classes were unknown, as is often the case with incremental detection.

All experiments are implemented in Python 3.7.3 and Pytorch 1.6.0 and conducted on a 64 core Intel Xeon CPU E5-2680 v4@2.40GHz with 512GB RAM and 1×NVIDIA TITAN RTX GPU.

4.1.4 Evaluation Metrics

We use three clustering metrics to evaluate the performance of the models: normalized mutual information (NMI), adjusted mutual information (AMI), and adjusted Rand index (ARI). NMI measures the amount of information one can extract from the distribution of the predictions and has been broadly adopted in event detection method evaluations. However, NMI is not adjusted for chance. Thus, we also select AMI, which is a more recent proposition. ARI considers all prediction label pairs and counts pairs that are assigned in the same or different clusters.

4.2 Multilingual Social Event Detection

We begin by the multilingual social event detection experiments, studying how the multilingual GNN detection framework deals with multilingual data. To show the performance of the framework more intuitively, we have reported the results of KPGNN for each monolingual component as well as for the full multilingual dataset to make comparison. For KPGNN on the whole multilingual data, the multilingual message graph is constructed through node-level alignment but without semantic-level alignment, which means, we get the initial node representations calculated by original language models. For example, we use the pre-trained English word embeddings to get representations of the English messages and use the pre-trained French and Arabic word embeddings to calculate the French and Arabic message representations. Note that our multilingual GNN detection framework additionally combines semantic-level alignment. To further measure the effectiveness of the cross-lingual module, we propose two model variants: KPGNN+Linear and KPGNN+NonLinear. With KPGNN+Linear, we use the corresponding French→English and Arabic→English cross-lingual language models obtained by MUSE to calculate the initial attribute features of the French and Arabic messages. Similarly, with KPGNN+NonLinear, we leverage the non-linear CLWE method LNMAP to obtain the initial attribute features of the French and Arabic parts. The corresponding transformations are pre-trained. The splits for the training, validation, and testing sets are 70%, 10%, and 20%, respectively.

4.2.1 Offline Evaluation

As shown in the lower part of Table 2, KPGNN+Nonlinear yields the best results. This may be because, in most real-world cases, there are no totally isomorphic language pairs so nonlinear transformations are more appropriate. Further, the better performance of KPGNN+Nonlinear over
### Methods

| Data          | Methods      | Metrics     |
|---------------|--------------|-------------|
|               |              | NMI         | AMI         | ARI         |
| English part  | KPGNN        | .81±.02     | .72±.02     | .42±.02     |
| French part   | KPGNN        | .69±.01     | .47±.01     | .27±.01     |
| Arabic part   | KPGNN        | .63±.01     | .37±.01     | .21±.02     |
| ALL           | KPGNN+M-BERT | .63±.02     | .51±.02     | .30±.01     |
|               | KPGNN+Linear (ours) | .52±.02   | .37±.02     | .19±.01     |
|               | KPGNN+Nonlinear (ours) | .64±.02 | .53±.02     | .33±.01     |

#### Table 2: Offline evaluation results on multilingual dataset and each monolingual part.

| Data          | Blocks | $M_1$ | $M_2$ | $M_3$ | $M_4$ | $M_5$ | $M_6$ |
|---------------|--------|-------|-------|-------|-------|-------|-------|
| English part  | # of messages | 894   | 2730  | 903   | 1514  | 930   | 1561  |
|               | # of events   | 36    | 46    | 32    | 36    | 39    | 51    |
| French part   | # of messages | 460   | 1378  | 441   | 747   | 484   | 748   |
|               | # of events   | 35    | 44    | 28    | 33    | 36    | 46    |
| Arabic part   | # of messages | 458   | 1338  | 419   | 769   | 492   | 784   |
|               | # of events   | 36    | 40    | 29    | 36    | 34    | 45    |
| All           | # of messages | 1812  | 5446  | 1763  | 3030  | 1906  | 3093  |
|               | # of events   | 41    | 48    | 33    | 42    | 45    | 53    |

#### Table 3: The statistics of multilingual social stream and each monolingual part.

KPGNN+M-BERT suggests that the CLWE methods have better generalizability when it comes to these three languages. Instead of learning a new joint vector space for all languages, as is the case with M-BERT, the cross-lingual module learns a specific transformation for each non-English-English pair, which is more accurate. This further demonstrates the merit of incorporating the cross-lingual module into the framework. Notably, none of the other baselines could bridge the divide between their monolingual design and this multilingual experiment. To see the effectiveness of the multilingual GNN detection framework in a relatively clear way, look to the results of the monolingual experiments with KPGNN in the upper part of Table 2. With the non-linear cross-lingual module, KPGNN+Nonlinear gets .64±.02 in NMI, .53±.02 in AMI, and .33±.01 in ARI on the whole dataset, surpassing the results of KPGNN on the Arabic part only and French part only in general even though the whole multilingual dataset consists of three languages and the data amount is largest.

#### 4.2.2 Incremental Evaluation

To evaluate the online setting, we split the multilingual dataset (one week of tweets) into individual days to construct a social stream. The first message block $M_1$ is used as the initial graph. Table 3 gives the statistics for the following blocks broken into the English, French, and Arabic components, along with the total. Table 4, 5, 6 show the results of the experiments.

As shown in Table 4, 5, 6, consistent with the offline evaluation, in general, KPGNN+Nonlinear yields the best results, surpassing KPGNN+Linear and KPGNN+M-BERT. Tables 4 and 5 show that KPGNN+Nonlinear’s metrics for NMI and AMI with the full multilingual dataset are even equal to, if not better than, the monolingual results for French and Arabic. This is a highly encouraging result.

#### 4.3 Cross-lingual Social Event Detection

This section presents the results of the CLKD framework specified for the special cases of detection in one specific low-resource language. The report begins with the offline evaluation, followed by the incremental evaluation. The percents for training, validation and testing are also 70%, 10%, 20%.

#### 4.3.1 Offline Evaluation

Recall that, in offline situations, the CLKD framework follows a two-stage training strategy – first the teacher network is trained, then the student networks. Hence, in the first stage, we train a teacher network on the English Twitter dataset. Then we train the student networks on the non-English datasets (i.e., French and Arabic) while fixing the teacher network’s parameters. To explore how much knowledge the trained English teacher network could lend to the student networks, we record these results separately. Additionally, we experiment with directly inputting the student datasets into the pre-trained teacher network. The results are shown in Table 7. With .70±.02 NMI, .63±.01 AMI, and .23±.01 ARI, the teacher network on English produces outstanding results. On the French and Arabic datasets, the teacher network returns .50±.01 and .39±.01 NMI, respectively. Table 8 shows these values are better than most baselines, which suggests that the teacher does hold prior knowledge that could be transferred to the student networks.

Table 8 shows further validation of the effectiveness of the CLKD framework. Here, we train the French and Arabic student networks under the supervision of the teacher representations but without the cross-lingual module, denoted as KPGNN+Prior. KPGNN+Prior+Linear denotes the same implementation but with the linear cross-lingual module MUSE, and KPGNN+Prior+Nonlinear is with the non-linear cross-lingual module LNMAP. From careful review of these results, we observe the following: (1) The GNN-based methods (PPGCN, KPGNN) achieve much better results than the other baselines, which is due in large part to their ability to aggregate message attribute features and structural information. In general, KPGNN gains the best performance among all of the baselines. The backbone GNN model in this work is as same as KPGNN. (2) For the most part, the three variants of the Teacher-Student CLKD framework gain equal or better results than the original KPGNN model. This is because, under the supervision of the pre-trained teacher network, prior knowledge that helps detect events is transferred to the students to augment their training. The better performance of the model
TABLE 4: Incremental evaluation NMIs on the whole multilingual dataset and each monolingual part.

| Data             | Methods                        | $M_1$     | $M_2$     | $M_3$     | $M_4$     | $M_5$     | $M_6$     |
|------------------|--------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| English part     | KPGNN                          | .82±.00  | .57±.01  | .71±.01  | .68±.01  | .85±.01  | .78±.01  |
| French part      |                                | .71±.01  | .42±.02  | .52±.01  | .48±.01  | .67±.01  | .56±.01  |
| Arabic part      |                                | .69±.01  | .41±.02  | .47±.03  | .42±.02  | .56±.02  | .51±.02  |
| ALL              |                                | .50±.01  | .31±.02  | .39±.01  | .39±.01  | .52±.01  | .43±.01  |
|                  | KPGNN+M-BERT                   | .63±.01  | .39±.02  | .55±.02  | .43±.02  | .58±.02  | .50±.02  |
|                  | KPGNN+Linear (ours)            | .53±.02  | .31±.01  | .38±.04  | .40±.01  | .51±.01  | .44±.01  |
|                  | KPGNN+Nonlinear (ours)         | .59±.01  | .39±.01  | .50±.03  | .45±.01  | .56±.02  | .52±.01  |

TABLE 5: Incremental evaluation AMIs on the whole multilingual dataset and each monolingual part.

| Data             | Methods                        | $M_1$     | $M_2$     | $M_3$     | $M_4$     | $M_5$     | $M_6$     |
|------------------|--------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| English part     | KPGNN                          | .79±.00  | .52±.01  | .67±.01  | .66±.01  | .82±.01  | .74±.01  |
| French part      |                                | .63±.03  | .33±.03  | .42±.02  | .40±.02  | .58±.01  | .45±.01  |
| Arabic part      |                                | .60±.02  | .34±.02  | .37±.03  | .33±.01  | .46±.02  | .41±.02  |
| ALL              |                                | .47±.02  | .26±.02  | .33±.03  | .34±.02  | .47±.01  | .37±.01  |
|                  | KPGNN+M-BERT                   | .58±.02  | .35±.02  | .51±.01  | .39±.02  | .52±.01  | .45±.02  |
|                  | KPGNN+Linear (ours)            | .48±.02  | .28±.01  | .32±.03  | .35±.02  | .46±.01  | .38±.01  |
|                  | KPGNN+Nonlinear (ours)         | .59±.01  | .39±.01  | .50±.03  | .45±.01  | .56±.02  | .52±.01  |

TABLE 6: Incremental evaluation ARIs on the whole multilingual dataset and each monolingual part.

| Data             | Methods                        | $M_1$     | $M_2$     | $M_3$     | $M_4$     | $M_5$     | $M_6$     |
|------------------|--------------------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| English part     | KPGNN                          | .63±.00  | .12±.01  | .29±.01  | .29±.01  | .67±.01  | .46±.01  |
| French part      |                                | .58±.02  | .12±.03  | .26±.03  | .20±.02  | .46±.04  | .30±.03  |
| Arabic part      |                                | .56±.05  | .17±.01  | .20±.03  | .16±.03  | .50±.06  | .30±.03  |
| ALL              |                                | .27±.01  | .16±.02  | .22±.03  | .21±.03  | .32±.02  | .20±.01  |
|                  | KPGNN+M-BERT                   | .41±.02  | .08±.01  | .24±.03  | .16±.04  | .30±.02  | .24±.02  |
|                  | KPGNN+Linear (ours)            | .28±.02  | .14±.01  | .20±.02  | .19±.02  | .31±.02  | .20±.01  |
|                  | KPGNN+Nonlinear (ours)         | .39±.03  | .12±.01  | .25±.04  | .19±.02  | .33±.02  | .25±.02  |

TABLE 7: Pre-trained teacher network and knowledge prior.

| Model            | Metrics              | English Data | French Data | Arabic Data |
|------------------|----------------------|--------------|-------------|-------------|
| KPGNN(Teacher)   | NMI                  | .70±.02      | .50±.01     | .39±.01     |
|                  | AMI                  | .63±.01      | .42±.00     | .20±.01     |
|                  | ARI                  | .23±.01      | .11±.01     | .19±.02     |

TABLE 8: Offline Evaluation on French and Arabic datasets.

| Methods          | French Data | Arabic Data |
|------------------|-------------|-------------|
|                  | NMI AMI ARI | NMI AMI ARI |
| Word2Vec [31]    | 26±.00      | 23±.00      |
| BERT  [20]       | 33±.01      | 24±.00      |
| LDA [37]         | 26±.00      | 0.36±.00    |
| PP-GCN [17]      | 56±.02      | 48±.01      |
| EventX [15]      | 52±.00      | 58±.00      |
| KPGNN [19]       | 63±.01      | 59±.01      |
| KPGNN+Prior      | 64±.01      | 59±.01      |
| KPGNN+Prior + Linear | 66±.02  | 61±.01      |
| KPGNN+Prior + Nonlinear | 65±.01  | 59±.00      |
| promotion        | ↑ 3%        | ↑ 2%        |

with priors shows the effectiveness of the knowledge distillation framework. (3) On both the French and Arabic datasets, the variants with the cross-lingual module perform best, verifying the merits of this approach. On the French dataset, the variant with the linear cross-lingual module (KPGNN+Prior+Linear) delivers the best result, while, on the Arabic dataset, the variant with the non-linear cross-lingual module (KPGNN+Prior+Nonlinear) is the best. This linear variant may have been better with French because the French-English language pair comes closer to an isomorphic assumption. In other words, their vector spaces have a more similar geometric structure. The opposite is true of the English-Arabic pairs, so the non-linear variant is better suited to this task.

4.3.2 Incremental Evaluation

To create an online testing environment, we split the French and English datasets by dates to construct two parallel social streams. The Arabic dataset is not included in this experiment because it is not based on a time period but, rather, on events by class. For both selected datasets, we use the messages of the first week to form an initial message block $M_0$ and the messages from the remaining days to form the following message blocks. Recall that the French data spans a period of 23 days, and the English spans 29 days, so the goal of the task is to detect events in the French message blocks $M_1, M_2, \ldots, M_{16}$. The corresponding English message blocks $M_1, M_2, \ldots, M_{16}$ act as assistants, and blocks $M_{17}, M_{18}, \ldots, M_{22}$ are redundant.

As shown in Fig. 3 (b), armed with mutual guidance, the two networks are updated in a synchronous way. For
The pre-trained linear mapping is likely to suit most cases. Although French and English are very close, transformation is not the best choice. This is reasonable and acceptable because not every language pair is fully isomorphic. For some blocks, like $M_9$, a linear transformation is more appropriate for English-French pairs. For some blocks, like $M_7$, $M_9$, $M_{10}$, a linear transformation is not the best choice. This is reasonable and acceptable because not every language pair is fully isomorphic. Although French and English are very close, the pre-trained linear mapping is likely to suit most cases.

Table 10: Incremental evaluation NMIs on the French dataset.

| Blocks | $M_1$ | $M_2$ | $M_3$ | $M_4$ | $M_5$ | $M_6$ | $M_7$ | $M_8$ |
|--------|-------|-------|-------|-------|-------|-------|-------|-------|
| Word2Vec [31] | .22±.00 | .22±.00 | .25±.00 | .28±.00 | .48±.00 | .33±.00 | .35±.00 | .37±.00 |
| BERT [20] | .32±.00 | .32±.00 | .31±.00 | .33±.00 | .47±.00 | .36±.00 | .41±.00 | .44±.00 |
| LDA [37] | .20±.00 | .09±.00 | .13±.00 | .10±.00 | .24±.00 | .22±.00 | .12±.00 | .24±.00 |
| PP-GCN [17] | .49±.01 | .45±.00 | .56±.03 | .54±.03 | .54±.02 | .52±.02 | .56±.04 | .56±.03 |
| EventX [6] | .34±.00 | .37±.00 | .37±.00 | .39±.00 | .53±.00 | .44±.00 | .41±.00 | .54±.00 |
| KPGNN+Prior | .54±.01 | .56±.02 | .52±.03 | .55±.01 | .58±.02 | .59±.03 | .63±.02 | .58±.02 |

promotion: ↑ 3% ↑ 4% ↑ 5% ↑ 2% ↑ 4% ↑ 4% ↑ 3% ↑ 3%

The results for the French dataset are summarized in Table 10 (NMI, AMI, ARI). The CLKD framework yields better results than KPGNN and the other baselines in almost all message blocks, which demonstrates the advantages of using English priors as a training assistant with low-resource languages. Further analyzing the results, we can see that, for most message blocks, the best performance is obtained with the linear cross-lingual module. This is consistent with our observation in the offline experiments that a linear transformation is more appropriate for English-French pairs. For some blocks, like $M_7$, $M_9$, $M_{10}$, a linear transformation is not the best choice. This is reasonable and acceptable because not every language pair is fully isomorphic. Although French and English are very close, the pre-trained linear mapping is likely to suit most cases but “most” does not mean “all”.

4.4 Time Consumption

To demonstrate that the proposed CLKD framework is practical and can be used for scalable training, we con-
### TABLE 11: Incremental evaluation AMIs on the French dataset.

| Blocks                  | $M_9$ | $M_{10}$ | $M_{11}$ | $M_{12}$ | $M_{13}$ | $M_{14}$ | $M_{15}$ | $M_{16}$ |
|------------------------|-------|----------|----------|----------|----------|----------|----------|----------|
| Word2Vec [31]          | .56±.00 | .56±.01 | .52±.02 | .56±.01 | .58±.02 | .55±.02 | .59±.01 | .62±.01 | .59±.02 |
| KPGNN+Prior            | .57±.02 | .59±.00 | .59±.01 | .59±.00 | .59±.01 | .59±.01 | .59±.00 | .59±.01 | .59±.00 |
| KPGNN+Prior+Linear     | .51±.01 | .55±.02 | .53±.02 | .58±.01 | .56±.01 | .63±.01 | .59±.01 | .59±.00 | .59±.00 |
| promotion              | ↑ 3%   | ↑ 4%     | ↑ 4%     | ↑ 1%     | ↑ 2%     | ↑ 2%     | ↑ 2%     | ↑ 2%     | ↑ 2%     |
| Word2Vec [31]          | .46±.02 | .56±.02 | .53±.01 | .56±.02 | .60±.02 | .65±.02 | .58±.02 | .50±.01 | .50±.02 |
| BERT [20]              | .46±.02 | .62±.01 | .58±.02 | .63±.01 | .66±.02 | .73±.01 | .67±.01 | .51±.03 | .53±.01 |
| KPGNN+Prior+Nonlinear  | .45±.01 | .61±.01 | .56±.01 | .62±.02 | .63±.02 | .68±.01 | .60±.01 | .53±.01 | .53±.01 |
| promotion              | ↑ 1%   | ↑ 7%     | ↑ 1%     | ↑ 5%     | ↑ 6%     | ↑ 8%     | ↑ 9%     | ↑ 1%     | ↑ 1%     |

### TABLE 12: Incremental evaluation ARIs on the French dataset.

| Blocks                  | $M_9$ | $M_{10}$ | $M_{11}$ | $M_{12}$ | $M_{13}$ | $M_{14}$ | $M_{15}$ | $M_{16}$ |
|------------------------|-------|----------|----------|----------|----------|----------|----------|----------|
| Word2Vec [31]          | .08±.00 | .10±.00 | .16±.00 | .11±.00 | .25±.00 | .13±.00 | .15±.00 | .18±.00 |
| BERT [20]              | .09±.00 | .14±.00 | .17±.00 | .12±.00 | .22±.00 | .12±.00 | .16±.00 | .18±.00 |
| LDA [17]               | .01±.00 | .04±.00 | .01±.00 | .06±.00 | .02±.00 | .05±.00 | .04±.00 | .04±.00 |
| PP-GCN [17]            | .27±.03 | .21±.01 | .38±.03 | .35±.05 | .30±.01 | .27±.02 | .38±.05 | .38±.04 |
| EventX [6]             | .01±.00 | .01±.00 | .01±.00 | .01±.00 | .01±.00 | .01±.00 | .01±.00 | .01±.00 |
| KPGNN [19]             | .29±.02 | .37±.01 | .39±.04 | .36±.04 | .37±.02 | .35±.04 | .37±.02 | .38±.02 |
| KPGNN+Prior            | .28±.04 | .38±.04 | .31±.01 | .35±.03 | .37±.02 | .31±.02 | .37±.02 | .37±.03 |
| KPGNN+Prior+Linear     | .31±.02 | .39±.02 | .41±.04 | .40±.04 | .40±.02 | .36±.02 | .34±.05 | .36±.02 |
| KPGNN+Prior+Nonlinear  | .29±.02 | .35±.03 | .35±.07 | .32±.06 | .38±.03 | .35±.02 | .39±.01 | .39±.02 |
| promotion              | ↑ 2%   | ↑ 2%     | ↑ 2%     | ↑ 4%     | ↑ 3%     | ↑ 1%     | ↑ 1%     | ↑ 1%     |

| Blocks                  | $M_9$ | $M_{10}$ | $M_{11}$ | $M_{12}$ | $M_{13}$ | $M_{14}$ | $M_{15}$ | $M_{16}$ |
|------------------------|-------|----------|----------|----------|----------|----------|----------|----------|
| Word2Vec [31]          | .10±.00 | .20±.00 | .13±.00 | .19±.00 | .07±.00 | .17±.00 | .20±.00 | .11±.00 |
| BERT [20]              | .10±.00 | .13±.00 | .10±.00 | .24±.00 | .08±.00 | .18±.00 | .17±.00 | .11±.00 |
| LDA [17]               | .01±.00 | .02±.00 | .03±.00 | .05±.00 | .01±.00 | .03±.00 | .10±.00 | .01±.00 |
| PP-GCN [17]            | .32±.04 | .37±.04 | .37±.04 | .39±.03 | .39±.01 | .39±.06 | .40±.06 | .26±.03 |
| EventX [6]             | .01±.00 | .02±.00 | .01±.00 | .02±.00 | .01±.00 | .02±.00 | .02±.00 | .01±.00 |
| KPGNN [19]             | .23±.02 | .38±.02 | .25±.02 | .46±.02 | .36±.05 | .50±.03 | .37±.02 | .26±.02 |
| KPGNN+Prior            | .27±.03 | .45±.05 | .24±.03 | .44±.01 | .38±.01 | .58±.02 | .44±.01 | .22±.03 |
| KPGNN+Prior+Linear     | .23±.02 | .40±.03 | .28±.03 | .51±.01 | .40±.04 | .60±.03 | .50±.05 | .27±.03 |
| KPGNN+Prior+Nonlinear  | .23±.01 | .40±.03 | .27±.01 | .50±.01 | .39±.01 | .59±.03 | .44±.03 | .23±.01 |
| promotion              | ↓ 5%   | ↑ 7%     | ↓ 9%     | ↑ 5%     | ↑ 1%     | ↑ 10%    | ↑ 10%    | ↑ 1%     |
duct some time trials of the CLKD on the French dataset in an online setting. Fig. 5 shows the results. We use a mini-batch sampling strategy during the training process, recording the time for one mini-batch. As the cross-lingual language models are pre-trained, the transformed attribute features are obtained at the data processing stage. Thus, the time consumption for the three variants with knowledge distillation is the same. KPGNN+Prior is used to represent all three variants. For a more intuitive comparison, we also record the time KPGNN needed to process a French message block and a corresponding English message block, denoted as KPGNN_F and KPGNN_E, respectively. As shown in Fig. 5 and consistent with the time complexity analysis in Section 3.5, the time needed for the CLKD framework to process the combined data stream is almost equal to the sum of KPGNN_F and KPGNN_E. Moreover, as discussed in Section 3.4, we only use the newest message block data for training in the maintenance stage. Hence, obsolete nodes are deleted and the training regime stays light. Overall, these results prove that the CLKD framework can be used for scalable training.

4.5 Visualization
To give a more intuitive comparison, and to further show the extent to which knowledge distillation and the cross-lingual module helps the event detection process, we prepare visualization of the Arabic Twitter dataset. For this, we plot the representations of the test set using t-SNE [39] using calculated message embeddings from: Word2Vec and BERT; the output embeddings from the last layer of PP-GCN and KPGNN; and the same from our variants with knowledge distillation, i.e., KPGNN+Prior, KPGNN+Prior+Linear, and KPGNN+Prior+Nonlinear. The results are shown in Fig. 6. Noted that in the Arabic Twitter dataset, there are 7 events in total: the Jordan floods, Kuwait floods-18, Hafr Albatin floods-19, the Cairo bombing, the Dragon storms, the Beirut explosion, and the Beirut explosion.
and Covid-19. Each color in Fig. 8 represents an event. Comparing Fig. 6(a) and (b) with (c) and (d), it is obvious that the results are worse in (a) and (b). Thus, we conclude GNN-based methods are better than the methods that rely purely on learning message representations, i.e., Word2Vec and BERT. As explained, this is largely due to the expressive power of GNNs at capturing structural information and rich semantics at the same time. Comparing Fig. 5(d) with (e), (f), and (g), we can see that the three variants that learn with prior knowledge do better. This demonstrates the effectiveness of knowledge distillation. What’s more, the variants that incorporate the cross-lingual module, Figs. 6(f) and (g), have more distinct boundaries than (e), which speaks to the importance of the cross-lingual module.

4.6 Hyper-parameter Analysis

Analysis of the weight of knowledge distillation loss $\lambda$. $\lambda$ is the most important hyper-parameter to tune in the objective function of the CLKD framework. Fig. 7(a), (b), (c) demonstrate how the performance of the CLKD framework (Teacher-Student) is affected by the choice of $\lambda$ on the Arabic dataset in the offline situation, and Fig. 7(d), (e), (f) show the performance on the French dataset. We validate different values of $\lambda$ ranging from 0.1 to 1.0 (0.1, 0.5, 1.0), noting that the choice of $\lambda$ affects the optimization process. With a large value, the KD loss will play a more important role, which means getting more efferences from the teacher network to the student. The pre-trained teacher network gains great results in detecting events from student language data. Hence, $\lambda = 1.0$ should be chosen in offline situations. This is borne out in the result. On the French dataset, when $\lambda = 1.0$, with .66 NMI, .61 AMI, .35 ARI, KPGNN+Prior+Linear provides the best performance. On the Arabic dataset, the same is true but of KPGNN+Prior+Nonlinear, with .81 NMI, .80 AMI, .82 ARI. When $\lambda$ is small, the results on the French dataset are less affected comparing to the Arabic dataset. Fig. 8 shows the results for the French dataset in a mutual learning scheme with varying $\lambda$. We focus on the results of KPGNN+Prior+Linear, which shows best performance in the English and French language pair. As shown in Fig. 8(b), for most message blocks, the choice of $\lambda$ doesn’t make differences to the NMI, AMI and ARI results. The three lines basically coincide. Hence, we can get the conclusion that the CLKD framework in mutual learning structure shows robust performance at all $\lambda$ values on the French dataset.

Analysis of the maintaining window size $w$. $w$ determines the model update frequency when dealing with online social streams. Fig. 9 charts CLKD’s performance in mutual learning structure with different sizes of $w$. Generally, performance is better with a small $w$, such as $w = 1$ and $w = 3$. For example, with window sizes $w = 1, 3, 5$, the average NMI results of KPGNN+Prior+Linear are .63, .62, and .59, respectively. That is because smaller $w$ means more frequent model update. The model is updated in each
message block by continuously training with the current block data. In this way, the model is fully adapted to the social stream data. However, a small window size also requires more training time. For a good balance between performance and efficiency, we select \( w = 3 \) for our experiments.

5 RELATED WORK

Social Event Detection. According to survey \[39\], based on their objectives, social event detection can be broadly categorized as either feature-pivot (FP) \[41\] or document-pivot (DP) \[42\] methods. When separated by the techniques they use, social event detection methods can be divided into incremental clustering \[11, 12, 13, 14\], community detection \[5, 6, 16, 7, 8, 9\] and topic modeling \[10, 11, 12, 13, 14\]. More recently, with the great success of Graph Neural Networks \[43\], there has been a move towards GNN-based social event detection \[17, 18, 19\]. Authors \[17\] use Graph Convolutional Network as their event categorization model. Scaling to incremental setting, Authors \[19\] leverage inductive GNNs to extract information. Compared to early studies, GNN-based methods show their superiority in knowledge acquisition and preservation. However, although GNN-based models achieve fairly high accuracy, their application to date has been heavily restricted to high-resource monolingual data – especially English. Only few works focus on non-English languages. Authors \[29\] provide a french corpus annotated for event detection tasks and Authors \[44\] use linear SVM for detection on an Indian dataset. There is still no effective deep learning framework generalized for event detection tasks with any low-resource languages. Also, existing multilingual event detection methods \[7\] are not capable to fully utilize the rich information in social streams. In this work, we propose a novel multilingual social graph construction strategy that makes GNN models compatible with multilingual social media data, and propose the CLKD framework to segment detection for low-resource languages.

Knowledge Distillation. Knowledge distillation is initially adopted for model compression \[45\], to learn a compact student model from a larger teacher model \[46\] by letting the student imitate the output of teacher. The extra supervision extracted from the teacher includes the forms of class posterior probabilities \[46\], feature representations \[47, 48\], or inter-layer flows (the inner product of feature maps) \[49\]. To penalize the difference between student and teacher, the distillation loss can be considered as cross entropy loss, Kullback-Leibler (KL) divergence loss, etc. Noticed that classical Teacher-Student distillation methods follow an offline training strategy that involves two
phases of training. Authors [36] overcome this limitation with a one-phase online training regime that distills knowledge between two student models acting as peers to each other. Recently, there has been a rising interest in cross-modality knowledge distillation which transfers supervision across modalities, see [27], [50], [51]. Authors [51] devise a mutual knowledge distillation scheme that exploits prior knowledge learned from a source modality to improve the performance in target modality - the goal being to overcome is annotation scarcity. We share a similar philosophy but treat different languages as different modalities. To further alleviate the language barrier, we propose a cross-lingual module in our knowledge distillation framework.

Cross-Lingual Word Embeddings. Cross-Lingual Word Embeddings (CLWE) methods learn a shared word vector space, where words with similar meanings result in similar vectors regardless of the language they are originally expressed in. Early CLWE methods have been dominated by projection-based methods [52]. These approaches learn a linear projection by minimizing the distance between translation pairs in a training dictionary. The requirement of dictionary is later reduced with self-learning [53], and then removed via unsupervised initialization heuristics [34], [35] and adversarial learning [55], [25]. Almost all these methods inherently assume that the embedding spaces of the different languages are approximately isomorphic, i.e., that they are similar in geometric structure. However, this simplified assumption has been questioned by researchers recently. Authors [55], [57] attribute the performance degradation of existing CLWE methods to the strong mismatches in embedding spaces caused by the linguistic and domain divergences. Due to this, authors [26] propose a novel non-linear CLWE method based on two auto-encoders. In this work, we pay attention to use a proper transformation between language pairs in social event detection tasks.

6 CONCLUSION

In this study, we focus on social event detection in multilingual social media streams. We address this task by combining entity alignment and a cross-lingual module with a GNN encoder. To overcome the scenarios where there is a lack of ample training data, as is the case with low-resource languages, we have devised a novel cross-lingual knowledge distillation framework (CLKD) to borrow prior knowledge learned from the high-resource English language. The merits of this approach are demonstrated in experiments with real and synthetic datasets. A particularly interesting future research direction would be the cross-lingual event propagation.

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