Designing weighted and multiplex networks for deep learning user geolocation in Twitter

Federico M. Funes
Facultad de Ingeniería (UBA)
ffunes@fi.uba.ar

José Ignacio Alvarez-Hamelin
Facultad de Ingeniería (UBA)
INTECIN (UBA-CONICET)
ihameli@cnet.fi.uba.ar

Mariano G. Beiró
Facultad de Ingeniería (UBA)
INTECIN (UBA-CONICET)
fbeiro@fi.uba.ar

Abstract

Predicting the geographical location of users of social media like Twitter has found several applications in health surveillance, emergency monitoring, content personalization, and social studies in general. In this work we contribute to the research in this area by designing and evaluating new methods based on the literature of weighted multigraphs combined with state-of-the-art deep learning techniques. The explored methods depart from a similar underlying structure (that of an extended mention and/or follower network) but use different information processing strategies, e.g., information diffusion through transductive and inductive algorithms –RGCNs and GraphSAGE, respectively– and node embeddings with Node2vec+. These graphs are then combined with attention mechanisms to incorporate the users’ text view into the models. We assess the performance of each of these methods and compare them to baseline models in the publicly available Twitter-US dataset; we also make a new dataset available based on a large Twitter capture in Latin America. Finally, our work discusses the limitations and validity of the comparisons among methods in the context of different label definitions and metrics.

1 Introduction

User geolocation in social media platforms has proven a useful resource for the development of tools for public health surveillance (e.g., monitoring of ailing ailments and symptoms (Paul and Dredze, 2011); forecasting of zika virus incidence (McGough et al., 2017)) and of emergency monitoring systems (e.g., earthquakes (Sakaki et al., 2010); forest fires (De Longueville et al., 2009); floods (Jongman et al., 2015)). However, many social media such as Twitter do not provide wide access to their users’ location information: i.e., the location field in the Twitter user profile is unstructured and noisy, and thus difficult to map to a real location. It has also been assessed that only \( \sim 1\% \) of the tweets are geotagged (Cheng et al., 2010), making it challenging to automatically link the large flow of real-time information available through the platform to specific places.

These limitations motivate the study of location prediction in Twitter based on the information that is available on the platform, such as the content published by the users, the hashtags they use, and the users they mention, reply to, or follow. This task can be enriched by combining techniques from a variety of areas, such as Natural Language Processing, social networks and graph mining.

The literature on user geolocation in Twitter has developed several graph-based and content-based deep learning models in the last years, while it also proposed the usage of specific metrics as \( \text{Acc@100} \), and alternative label construction techniques as the usage of \( k-d \) trees. Many works also explored the usage of probabilistic classifiers and information-theoretic or statistic measures for detecting Location Indicative Words (LIW’s), and the remotion of celebrities from the contact graphs. We make a brief historical account of these advances in Section 5.

2 Data collection and preprocessing

In this work we introduce a dataset collected between January 1, 2019 and December 10, 2019 in Argentina using the Twitter API, in the context of a social study (Reyero et al., 2021). The users’ set was defined as those Twitter accounts who were following at least one of the candidates for the Argentinian presidential elections during 2019, which made for a total of 900 million tweets captured, belonging to 2 million active users. For each user, all her tweets were collected, unless she had posted more than 3,000 tweets between two consecutive polls (around 5 days) –something which happened with extremely low frequency– in which case her tweets were automatically capped by the API.

From these 900 million tweets, around 1 mil-
lion were precisely geolocalized by a set of coordinates in the metadata; this statistic is consistent with previous findings (e.g., (Cheng et al., 2010)). Moreover, 14 million tweets had metadata that geolocalized them inside a bounding box and mentioned a specific city chosen by the user when tweeting. We unified and validated the latter by combining the information with the Geonames gazzetteer (https://www.geonames.org/), assigning a city in Geonames and a set of precise coordinates to each geolocated tweet. In this process, around 2 million tweets had to be discarded.

For each user with at least one geolocated tweet, we defined her ground-truth location as the city in which most of her geolocated tweets were placed. At this point, we built the two labelled datasets described in Table 1. The tweet ids composing each of these datasets are publicly available at GitHub1 for hydration. Compared to previous datasets in the literature, our datasets offer a higher average of tweets per user (around 1,000), thus providing a large volume of content data for training.

Our datasets Twitter-ARG-Exact and Twitter-ARG-BBox cover 95 and 229 cities across 14 and 22 different countries respectively (with at least 100 users in each city), but most of the users (76.9% and 72.6% respectively) lie inside Argentina.

2.1 Profile location analysis
We analyzed the veracity of the location informed by the users in their profile. (Cheng et al., 2010) had found that only 26% of the users mention a city in their profile location field. We applied a tokenizer to the location field and tried to match the words to a city and/or country name in GeoNames. We found a match with one or more GeoNames cities for 63% of our users who had some profile location information available. Interestingly, for those with only one match (40.9% of the total users), it turned out that 52% of them were coincident with the ground-truth location obtained from their georeferenced tweets. All in one, this implies that only 20% of our users have an unambiguous city in their location profile that matches their geolocated tweets.

Figure 1 shows the distribution of distances between the profile city and the ground-truth one extracted from the geolocated tweets, for those users whose profile city is unambiguous. We observe that 65% of these users have an error of less than 10km between their profile location and their ground-truth one. However, 25% of the users have an error larger than 161km, which is the typical relaxed accuracy bound in the location prediction literature, and thus we consider that the profile location is not accurate enough for building ground-truth city labels.

2.2 Graphs’ construction
Exploiting the mentions contained in the users’ tweets, and the users’ following relationships extracted through the Twitter API, we built user networks that can help predict their locations.

Frequently, users in our dataset will follow or mention users which are not part of it. Although we could discard these connections, they might be relevant for inferring the user’s location: e.g., if two users follow many people in common, their probability of being geographically close is larger than for a pair of random users.

Given the set of users in our dataset, \( U \), and the extended set of users \( E \) obtained by adding users mentioned by those in our dataset, we denote \( n = | U | \) and \( m = | E | \), and we consider the mention matrix \( M \in \mathbb{R}^{n \times n} \) which represents a weighted directed graph with no loops, whose nodes are those users in \( U \). The elements \( m_{ij} \) in this matrix point out the number of times that user \( i \) mentioned user \( j \) in her tweets.
Table 1: Basic statistics for the datasets introduced in this work.

| Dataset            | Users | Geolocated tweets | Total tweets |
|--------------------|-------|-------------------|--------------|
| Twitter-ARG-Exact  | 37,146| 625,180           | 27,574,343   |
| Twitter-ARG-BBox   | 141,209| 9,298,954        | 124,192,146  |

Previous works in the literature obtain a collapsed mention matrix that adds co-mentions to the mention network, by computing \((M+I) \cdot (M+I)^T\) (see, e.g., (Rahimi et al., 2015, 2018)).

In this work we propose an alternative solution that combines the connections in the mention graph \(M\) with mention paths that traverse users outside our user set; this procedure gives a weighted graph as result. We define our extended mention network as \(Y = (M+M^T)+(X_M \cdot X_M^T - \text{diag}(X_M \cdot X_M^T))\). Here, \(X_M \in 1^{n \times (m-n)}\) represents the existence of mentions from users in \(U\) to users not in \(U\), and thus corresponds to a bipartite graph. The left term in the formula represents the symmetrized mention matrix (where each element \(a_{ij}\) represents the number of times that users \(i\) and \(j\) mention one another), while the right term represents the number of users external to our dataset that both \(i\) and \(j\) mention. Thus, the latter extends the mention network by adding co-mentions going through external users. Following (Rahimi et al., 2015) we remove mentions to popular users before computing our extended network.

The advantages of this extended network with respect to the previous collapsed networks’ definitions are two-fold: firstly, it can simultaneously weight mentions and co-mentions in the results – thus profiting of all the mention information that we collect in tweets– and secondly, that it reduces the complexity of the obtained network –in (Rahimi et al., 2015) and (Rahimi et al., 2018), for example, \(n\) nodes mentioning a central node in the training/test set generate \(n \cdot (n-1)\) edges in the collapsed network–. We illustrate our procedure in Figure 2.

When the follower network is available –as is the case in our dataset– we also extend it by including connections to users outside our dataset. We define our extended follower network as \(Z = F + (X_F \cdot X_F^T - \text{diag}(X_F \cdot X_F^T))\). Here, \(X_F \in 1^{n \times (m-n)}\) represents follower relationships from users in \(U\) to users not in \(U\). Put into words, this computation extends the follower network by adding co-follower relationships to external users (i.e., counting the number of users outside our dataset that are co-followed by a pair of users \(i\) and \(j\) in our dataset). We treat the resulting network as undirected and weighted, and we also remove popular nodes from the original data before computing \(Z\).

In one of our models, RGCN-EXT, both the extended mention graph and the extended follower graph are combined into a multiplex graph (Kivelä et al., 2014). In this type of graph, the set of nodes is the same across all layer, but each layer represents a different relationship type; thus, the network can couple the information diffusion paths provided by each layer. This could be further generalized to allow the flow of information across layers as in general multilayer graphs, or to decompose layers into sublayers (e.g., dividing the mention layer into pure mentions and external comenton).

2.3 Labels construction

In most cases, ground-truth location labels lie on a continuous space given by the precise latitude and longitude coordinates –e.g., in our Twitter-ARG-Exact dataset–. In order to discretize these labels, (Roller et al., 2012) proposed the usage of \(k\)-\(d\) trees (Bentley, 1975). This method builds equally-sized partitions of space which can improve the classifiers’ learning task.

The usage of \(k\)-\(d\) trees also has some pitfalls: if many users share the same set of coordinates (i.e., due to precision limitations), it becomes hard
to obtain similarly sized fine-grained partitions; also, in the presence of very dense metropolitan areas, they might be split into several $k$-$d$ regions during partitioning, thus confusing the classifiers, as several leaf nodes will refer to quite similar users or locations. A discussion of this point can be found in (Han et al., 2012).

For the Twitter-ARG-BBox dataset, we discarded using $k$-$d$ trees due to the former reason. For Twitter-ARG-Exact, instead, we evaluated both methods, but we found that the usage of $k$-$d$ trees was outperformed by city labels, due to the large number of samples in the Buenos Aires metropolitan area. In Figure 3 we show the division that a $k$-$d$ tree would produce on our dataset Twitter-ARG-Exact.

For Twitter-US, instead we will show results for both labels types, $k$-$d$ tree nodes and city names, for the sake of comparison.

3 Models

We propose 3 graph-based geolocation models: (a) RGCN-EXT, a Relational Graph Convolutional Network that combines mentions and follower relationships as different layers of a multiplex, (b) GraphSAGE-EXT, an inductive learning model based on GraphSAGE and, (c) N2V-EXT, a weighted graph embedding based on Node2vec+. All these models incorporate tweets’ content information in some step of their pipelines, as described in the following subsections. We also incorporate two content-based methods for comparison: BiLSTM-TXT, based on a bidirectional Long Short-Term Memory (Bi-LSTM), and Trans-TXT, based on a transformer’s encoder.

3.1 RGCN-EXT

Relational Graph Convolutional Networks (R-GCN’s) (Schlichtkrull et al., 2018) constitute an extension to GCN’s in which nodes can hold several types of relationships between them. In network theory, this concept is known as a multiplex network.

Each neural layer in an R-GCN is computed as:

$$
    h^{(l+1)}_i = \sigma \left( \sum_{r \in \mathcal{R}} \sum_{j \in \mathcal{N}_r^i} \frac{1}{c_{i,r}} W_r^{(l)} h^{(l)}_j + W_0^{(l)} h^{(l)}_i + b \right)
$$

where $\mathcal{R}$ represents the set of relationship types and $\mathcal{N}_r^i$ represents the set of neighbors of node $i$ with relationship type $j$. We use the relationships obtained from the extended, weighted mention graph, and those of the extended, weighted follower graph when available.

The normalization constants $c_{i,r}$ can be learned, as well as the $W_r^{(l)}$ matrices and the bias, $b$. The input vector $h^{(0)}_i$ for each node at the input layer is a feature vector for user $i$ denoting a score for each label. We use a ReLU activation function ($\sigma$) for the intermediate R-GCN layers and a softmax activation at the output layer.

The input scores $h^{(0)}_i$ are computed by training a transformer’s encoder over the users’ text view (as explained for the baseline models in Subsection 3.4) and combining its predictions with those given by Location Indicative Words (LIW’s). The list of LIW’s in each training set is built using $\chi^2$ tests as proposed in (Han et al., 2014).

The full procedure is illustrated in Figure 4; we implemented this model through the Stellar-Graph library (Data61, 2018), and we denote it as RGCN-EXT in our results.

3.2 GraphSAGE-EXT

GraphSAGE (Hamilton et al., 2017) is an inductive learning framework capable of generating embeddings based on each node’s local neighborhood’s
features. During this process, the model learns a set of aggregator functions that can later be used to make predictions for nodes that were not seen during training.

We apply this model to the extended, weighted mention graph using the MeanAggregator proposed in (Hamilton et al., 2017).

The aggregator at each node is computed as:

$$ h_i^{(l+1)} = \sigma \left( \mathbf{W}^{(l)} \cdot \left( h_i^{(l)} \sum_{j \in \mathcal{N}_i} h_j^{(l)} \right) / |\mathcal{N}_i| \right) . $$

The input vectors $h_i^{(0)}$ are computed as in the RGCN-EXT model, i.e., by scores obtained from training a transformer’s encoder over the users’ text view combined with the predictions made by Location Indicative Words (LIW’s).

In our GraphSAGE-EXT model, we use a ReLU nonlinearity as the $\sigma$ activation function, with a final softmax layer. We used the StellarGraph implementation (Data61, 2018) of GraphSAGE.

### 3.3 N2V-EXT

Node2vec (Grover and Leskovec, 2016) is a dimensionality reduction method that can learn node representations from graphs such that nodes at shorter distances in the graph tend to lie closer in the representation space; this is achieved by using biased random walkers.

In our model N2V-EXT we apply the weighted graph variant of Node2vec, Node2vec+ (Liu et al., 2021), to our extended mention graph and extended follower graph, using the implementation in (Liu and Krishnan, 2021). We combine the results of a logistic regression classifier for these embeddings with those of a transformer’s encoder on the users’ text view, by applying a logistic regression meta-classifier on the concatenation of both outputs.

### 3.4 Baseline content-based methods

We also implement two baseline models that only consider the users’ text view: BiLSTM-TXT and Trans-TXT.

In the BiLSTM-TXT model we use GloVe (Pennington et al., 2014) to extract embeddings from the content and train a BiLSTM to predict the location probabilities.

In the Trans-TXT model we train a transformer’s encoder (Vaswani et al., 2017) over the content. The input of this model is formed by the $d$-dimensional GloVe embeddings of the content generated by the user; the embedding matrix is also updated during training. A positional encoding is added to the input embedding and the result, $H \in \mathbb{R}^{n \times d}$, enters the encoder, which applies a multi-head attention layer and obtains a single representation $o$ for each user:

$$ o = \text{MultiHead}(Q, H) = [\text{head}_1, ..., \text{head}_h]W^O, $$
where:

$$\text{head}_i(Q, H) = \text{softmax} \left( \frac{QW^Q_i (HW^K_i)^T}{\sqrt{d_k}} \right) HW^V_i$$

The $W^Q_i$, $W^K_i$ and $W^V_i$ projections in each head $i$ are learnt during training, as well as the attention context $Q$ and the final projection $W^O$. The output of each head is of size $d_k = d/h$, and we use $h =$ 10 different heads for Twitter-US and $h = 6$ for our dataset. The output of the attention layer passes through a feed-forward and a softmax layer. These results are combined with the predictions made by Location Indicative Words (LIW’s) to train a meta-classifier.

We chose these two types of methods as they had been previously used to achieve the highest results in the literature (see (Huang and Carley, 2019)).

4 Results

In Table 2 we show the performance of the three proposed models (RGCN-EXT, GraphSAGE-EXT and N2V-EXT) and the two baselines, for our introduced dataset. We report the Acc@100, together with the mean and median errors. From these results we observe that the addition of network information produced a consistent improvement in performance, without any significant difference among the three methods. In this sense, we remark that GraphSAGE-EXT keeps the advantage of being an inductive algorithm, which makes it faster and more generalizable with respect to the other methods.

In Tables 3 we show the results for the Twitter-US dataset, either using city names or $k$-$d$ tree nodes as labels. We differentiate between the performance metrics obtained under different types of labels in order to make a fair comparison. In this sense, the label choice can strongly affect the results, as we observed for our own dataset. We compare against other methods in the literature that either use content information, or combine it with the users’ network. We do not compare against methods using metadata (e.g., the information in the user profile). Under tree-node labels, our results improved the state-of-the-art ((Miura et al., 2017)), while for city labels we obtained a slightly smaller accuracy as compared to (Huang and Carley, 2019), who proposed a hierarchical classifier –first predicting county, then city– that combined a Bi-LSTM on text embeddings and a network embedding.

5 Related work

One of the first works in the topic of user geolocation is the one by (Cheng et al., 2010), which proposes a model based on the probabilities of using each word in different cities or states. After refining their model by identifying Location Indicative Words (LIW’s) and smoothing the distributions, they reached an score of 51% of the users being assigned to a city closer than 100 miles to their ground truth location. This relaxed accuracy measure was later adopted by the literature and referred to as Acc@100 (accuracy at less than 100 miles).

Due to the uneven geographical distribution of the population in many countries, predicting the exact location (city, county or state) makes the classification problem highly unbiased. (Roller et al., 2012) was the first to propose using a grid based on a $k$-$d$ tree instead, in order to produce balanced classes. They obtained an Acc@100 of 0.346 on the Twitter-US dataset that they captured.

The selection of Location Indicative Words (LIW’s) was later improved by (Han et al., 2014), by comparing different statistical-based and information theory-based methods. The authors tested their method on the Twitter-US and Twitter-WORLD (Han et al., 2012) datasets, obtaining an Acc@100 of 0.450 and 0.270 respectively.

(Chi et al., 2016) built off (Han et al., 2014)’s work by adding city mentions and the top 10k Twitter @mentions and #hashtags to the LIW’s. Using a multinomial Naive Bayes model, they obtained an accuracy of 0.225, on the $W$-$NUT$ dataset. (Mahmud et al., 2014) used an ensemble of statistical and heuristic classifiers, and followed a hierarchical approach to predict time zone, state, and then city. They captured a dataset of 1.5M tweets generated by 9.5k users in 100 cities, and obtained an accuracy of 0.58 at the city level.

Some later works enhanced the performance by adding some type of network information into the models, based on the location homophily principle: users who are closer are more likely to establish connections and interact. (Rahimi et al., 2015, 2017) were the first to incorporate the @mention network into the prediction model: i.e., they built an undirected network in which two users $(u_1, u_2)$ are connected if one of them mentioned the other. They discarded mentions of highly popular users (e.g., celebrities) assuming that they would not be predictive of the follower’s location, and
they added edges by transitivity when the intermediate nodes were not part of the training/test set. They used a label propagation model based on Modified Adsorption (MAD, (Talukdar and Cramer, 2009)), reaching an Acc@100 of 0.61 for Twitter-US and 0.53 for Twitter-WORLD, using a k-d tree-based grid.

Other network-based models like (Miura et al., 2017) and (Huang and Carley, 2019) achieved an Acc@100 of 0.70 and 0.72 on Twitter-US respectively, by using neural network architectures and combining embeddings for the content, some metadata and the mention graph. (Rahimi et al., 2018) also explored the usage of a Graph Convolutional Network (GCN, (Kipf and Welling, 2017)) on the mention graph, obtaining an Acc@100 of 0.62 for Twitter-US and 0.54 for Twitter-WORLD.

Up to our knowledge, scarce works have used the follower network for location prediction in Twitter, possibly due to the fact that this type of data is difficult to obtain. (Li et al., 2012) collected this information for 140k users obtaining a follower network with 2 million edges; they fitted a probabilistic generative model obtaining an Acc@100 of 0.62. (Rodrigues et al., 2016) collected tweets from 12k users in Brazil, retrieving the last 200 tweets from each, and building a follower-followee graph with 125k edges. They obtained an accuracy of 0.652 when classifying the users into 10 Brazilian cities, using a Markov random field model that combined content and follower relationships. Finally, we mention that (Hemamalini et al., 2018), proposed an implementation for a location service based on follower information, but did not analyze any performance metrics or datasets. A thorough survey of the location prediction problem in Twitter can be found in (Zheng et al., 2018).

### Table 2: Cross-validated prediction results for the two Latin American datasets proposed here. We evaluate the results for our 3 proposed models combining network and content information, and we compare them with 2 content-based models.

| Method          | Twitter-ARG-Exact |          |           | Twitter-ARG-BBox |          |
|-----------------|-------------------|----------|-----------|------------------|----------|
|                 | Acc@100 ↑ | Mean ↓ | Median ↓ | Acc@100 ↑ | Mean ↓ | Median ↓ |
| **Content-based** |          |     |          |              |          |
| BiLSTM-TXT      | 0.750   | 547.5 | 5.2      | 0.496   | 989.9  | 191.6   |
| Trans-TXT       | 0.764   | 522.5 | 4.9      | 0.532   | 914.7  | 51.6    |
| **(Graph+content)-based** |          |     |          |              |          |
| RGCN-EXT        | 0.829   | 367.5 | 3.8      | 0.644   | 690.6  | 6.4     |
| GraphSAGE-EXT   | 0.823   | 369.1 | 3.8      | 0.578   | 798.4  | 23.2    |
| N2V-EXT         | **0.832** | 371.4 | 3.9      | **0.653** | 719.2  | 0       |

6 Conclusions

In this work we proposed three graph-based methods for user geolocation that can propagate users’ generated content through their extended mention and follower networks using different mechanisms: RGCN-EXT, GraphSAGE-EXT and N2V-EXT. In particular, the GraphSAGE-EXT model is trained under an inductive learning setting, thus avoiding retraining when new nodes appear in a real scenario.

We also proposed a new methodology for extending the mention graph with co-mentions towards third-users without overloading it, and we introduced the usage of the follower graph in some of our methods. Our results for the Latin America dataset suggest that the extended follower network, when available, can significantly improve the predictions as compared to the state-of-the-art baseline models; i.e., both the RGCN-EXT and N2V-EXT models obtained the best results in this case. The inclusion of the user text view in the models was performed through the encoder component of a transformer, this reduces the execution time as compared to other methods using recurrent neural network architectures.

On the other hand, in the well-known Twitter-US dataset our results improved the state of the art when using k-d tree nodes for building labels, while for city name levels, N2V-EXT stayed slightly below the results ob-
Method | Twitter-US (city labels) | Twitter-US (node labels) |
|-------|------------------------|-------------------------|
|       | Acc@100 | Mean | Median | Acc@100 | Mean | Median |
| BiLSTM-TXT | 0.508 | 638.9 | 150.8 | 0.500 | 603.1 | 161.7 |
| Trans-TXT | 0.523 | 653.6 | 132.4 | 0.513 | 589.3 | 146.7 |
| (Rahimi et al., 2017)-MLP | – | – | – | 0.54 | 554 | 120 |
| (Miura et al., 2017)-LR | – | – | – | 0.527 | 666.6 | 121.1 |
| (Huang and Carley, 2019)-HLPNN-Text | 0.571 | 516.6 | 89.9 | – | – | – |
| (Graph+content)-based |
| RGCN-EXT | 0.666 | 408.7 | 43.3 | 0.670 | 384.0 | 57.2 |
| GraphSAGE-EXT | 0.643 | 432.1 | 50.3 | 0.632 | 424.3 | 70.2 |
| N2V-EXT | 0.690 | 421.0 | 35.3 | 0.670 | 394.8 | 57.0 |
| (Rahimi et al., 2017)-MADCEL-W-MLP | – | – | – | 0.61 | 515 | 77 |
| (Miura et al., 2017)-MADCEL-B-LR | – | – | – | 0.601 | 582.8 | 66.5 |
| (Miura et al., 2017)-SUB-NN-UNET | 0.615 | 481.5 | 65 | – | – | – |
| (Rahimi et al., 2018)-MLP-TXT+UNET | – | – | – | 0.66 | 420 | 56 |
| (Huang and Carley, 2019)-HLPNN-NET | 0.708 | 361.5 | 31.6 | – | – | – |

Table 3: Cross-validated prediction results for the Twitter-US dataset, either with GeoNames cities (left) or nodes of a k-d tree (right) as prediction targets. When using node labels we consider the median of each region as its representative location, following (Rahimi et al., 2015). We evaluated the results for the 3 graph-based models and compared them against 2 proposed baseline models and others in the literature.

tained by (Huang and Carley, 2019) (significantly improving those obtained by (Miura et al., 2017), though).

By using two different georeference fields in the Twitter API’s –coordinates and bounding boxes– we measured the plausibility of training location models using bounding boxes, which are much more available that the precise tweet coordinates. While previous datasets in the literature are based on coordinates, we built a version of our dataset based on bounding boxes and reached an Acc@100 accuracy of 0.65. Also, we discussed the importance of analysing which is the best label construction technique in each case: for our proposed dataset, a large metropolitan area like Buenos Aires would be split into different nodes of a k-d tree. So, despite other advantages of the latter as the possibility of balancing class sizes, in this case it was more convenient to use cities as levels in order to obtain a smaller error. Also for the Twitter-US dataset, the best results were in general found at the city resolution level.

Future lines of research beyond this work include profiting of the multi-layer design of the R-GCN’s in order to introduce new layers (e.g., separating mentions from comentions, or incorporating a retweet network) and modeling the propagation of partially available features (e.g., profile information) with techniques as the ones proposed by (Rossi et al., 2021). Another interesting extension is to take into account users who are moving, either temporally (e.g., travelling) or due to migration or relocation. These factors could be taken into account by using embedding or diffusion methods based on temporal graphs.

Acknowledgements

The authors acknowledge the financial support of a PICT 2019 grant from the Agencia Nacional de Promoción Científica y Tecnológica (PICT 2019-01031).

References

Bentley, J. L. (1975). Multidimensional binary search trees used for associative searching. *Communications of the ACM*, 18(9):509–517.

Cheng, Z., Caverlee, J., and Lee, K. (2010). You are where you tweet: a content-based approach to geolocating twitter users. In *Proceedings of the 19th ACM international conference on Information and knowledge management*, pages 759–768.
Kipf, T. N. and Welling, M. (2017). Semi-supervised learning with graph convolutional networks. In Proceedings of the 2nd Workshop on Noisy User-generated Text (WNUT), pages 227–234.

Hemamalini, S., Kannan, K., and Pradeepa, S. (2018). Location prediction in social media data by finding location indicative words and textual features. In Proceedings of the 2018 International Conference on Artificial Intelligence Research.

De Longueville, B., Smith, R. S., and Luraschi, G. (2009). "omg, from here, i can see the flames!" a use case of mining location based social networks to acquire spatio-temporal data on forest fires. In Proceedings of the 2009 international workshop on location based social networks, pages 73–80.

Grover, A. and Leskovec, J. (2016). node2vec: Scalable feature learning for networks. In Proceedings of the 22nd ACM SIGKDD international conference on Knowledge discovery and data mining, pages 855–864.

Hamilton, W. L., Ying, R., and Leskovec, J. (2017). Inductive representation learning on large graphs. In Proceedings of the 31st International Conference on Neural Information Processing Systems, pages 1025–1035.

Han, B., Cook, P., and Baldwin, T. (2012). Geolocation prediction in social media data by finding location indicative words. In Proceedings of COLING 2012, pages 1045–1062.

Han, B., Cook, P., and Baldwin, T. (2014). Text-based twitter user geolocation prediction. Journal of Artificial Intelligence Research, 49:451–500.

Hemamalini, S., Kannan, K., and Pradeepa, S. (2018). Location prediction of twitter user based on friends and followers. International Journal of Pure and Applied Mathematics, 118(18):2817–2824.

Huang, B. and Carley, K. (2019). A hierarchical location prediction neural network for Twitter user geolocation. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4732–4742, Hong Kong, China. Association for Computational Linguistics.

Jongman, B., Wagemaker, J., Romero, B. R., and De Perez, E. C. (2015). Early flood detection for rapid humanitarian response: harnessing near real-time satellite and twitter signals. ISPRS International Journal of Geo-Information, 4(4):2246–2266.

Kipf, T. N. and Welling, M. (2017). Semi-supervised classification with graph convolutional networks. In International Conference on Learning Representations (ICLR).
Rahimi, A., Cohn, T., and Baldwin, T. (2018). Semi-supervised user geolocation via graph convolutional networks. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2009–2019. Association for Computational Linguistics.

Reyero, T. M., Beiró, M. G., Alvarez-Hamelin, J. I., Hernández, L., and Kotzinos, D. (2021). Evolution of the political opinion landscape during electoral periods. EPJ Data Science, 10(1):31.

Rodrigues, E., Assunção, R., Pappa, G. L., Renno, D., and Meira Jr, W. (2016). Exploring multiple evidence to infer users’ location in twitter. Neurocomputing, 171:30–38.

Roller, S., Speriosu, M., Rallapalli, S., Wing, B., and Baldrige, J. (2012). Supervised text-based geolocation using language models on an adaptive grid. In Proceedings of the 2012 joint conference on empirical methods in natural language processing and computational natural language learning, pages 1500–1510.

Rossi, E., Kenlay, H., Gorinova, M. I., Chamberlain, B. P., Dong, X., and Bronstein, M. (2021). On the unreasonable effectiveness of feature propagation in learning on graphs with missing node features.

Sakaki, T., Okazaki, M., and Matsuo, Y. (2010). Earthquake shakes twitter users: real-time event detection by social sensors. In Proceedings of the 19th international conference on World wide web, pages 851–860.

Schlichtkrull, M., Kipf, T. N., Bloem, P., Van Den Berg, R., Titov, I., and Welling, M. (2018). Modeling relational data with graph convolutional networks. In European semantic web conference, pages 593–607. Springer.

Talukdar, P. P. and Crammer, K. (2009). New regularized algorithms for transductive learning. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pages 442–457. Springer.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. (2017). Attention is all you need. In Advances in neural information processing systems, pages 5998–6008.

Zheng, X., Han, J., and Sun, A. (2018). A survey of location prediction on twitter. IEEE Transactions on Knowledge and Data Engineering, 30(9):1652–1671.