Geosemantic Network-of-Interest Construction Using Social Media Data

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Abstract. An ever increasing amount of geospatial data generated by mobile devices and social media applications becomes available and presents us with applications and also research challenges. The scope of this work is to discover persistent and meaningful knowledge from user-generated location-based "stories" as reported by Twitter data. We propose a novel methodology that converts geocoded tweets into a mixed geosemantic network-of-interest (NOI). It does so by introducing a novel network construction algorithm on segmented input data based on discovered mobility types. The generated network layers are then combined into a single network. This segmentation addresses also the challenges imposed by noisy, low-sampling rate "social media" trajectories. An experimental evaluation assesses the quality of the algorithms by constructing networks for London and New York. The results show that this method is robust and provides accurate and interesting results that allow us to discover transportation hubs and critical transportation infrastructure.

1 Introduction

An important resource in today's mapping efforts, especially for use in mobile navigation devices, is an accurate collection of point-of-interest (POI) data. However, by only considering isolated locations in current datasets, the essential aspect of how these POIs are connected is overlooked. The objective of this work is to take the concept of POIs to the next level by computing *Networks of Interest* (NOIs) that encode different types of connectivity between POIs and capture peoples type of movement and behavior while visiting these POIs. This new concept of NOIs has a wide array of application potential, including traffic planning, geomarketing, urban planning, and the creation of sophisticated location-based services, including personalized travel guides and recommendation systems. Currently, the only datasets that consider connectivity of locations are road networks, which connect intersection nodes by means of road links purely on a geometric basis. POIs however, encode both geometric and semantic information and it is not obvious how to create meaningful links and networks between them. We propose to capture, both, *geometric* and *semantic* information in one NOI by analyzing social media in the form of spatial check-in data. We use the concept of check-in as a generic term for users actively volunteering their presence at a specific location. Existing road maps and POIs encode mostly geometric information and consist of street

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maps, but may also include subway maps, bus maps, and hiking trail maps. To complement this dataset, *geometric trajectories* consist of geo-referenced trajectory data, such as GPS tracking data obtained from people moving on a road network. This type of data is assumed to have a relatively high sampling rate. Typical examples include vehicle tracking data sampled every 10 or 30 seconds. Such datasets are constructed using *map construction* (cf. [1], [2] for surveys).

In this work, we will use *behavioral trajectories* as a data source. They are obtained from social media in the form of spatial check-in data, such as geocoded tweets from Twitter. Similar to GPS tracking, the user contributes a *position sample* by checking in at a specific location. Compared to geometric trajectories, such check-in data result in very low-sampling rate trajectories that when collected for many users provide for a less dense, but semantically richer "movement network" layer. The main challenge arises from the fact that trajectories composed from geocoded tweets differ technically and semantically from raw GPS-based type of trajectories. Unlike trajectories obtained from GPS devices in typical tracking applications, such data are typically quite sparse since individuals tend to publish their positions only at specific occasions. However, we advocate that by combining and analyzing time and location of such data, it is possible to construct event-based trajectories, which can then be used to analyze user mobility and to extract visiting patterns of places. The expectation towards behavioral trajectories is that by integrating them into a Network of Interest, the resulting dataset will go beyond a homogeneous transportation network and will provide us with a means *to construct an actual depiction of human interest and motion dependent on user context and independent of transportation means*. As early maps were traces of people's movements in the world, i.e., view representations of people's experiences, NOIs try to fuse different qualities of such trace datasets obtained through intentional (e.g., social media, Web logs) or unintentional efforts (e.g., routes from their daily commutes, check-in data) to provide for a *consequent modern map equivalent*.

Specifically, in this paper we address the challenge of extracting a geosemantic NOI from noisy, low-sampled geocoded tweets. To do so, we introduce a new NOI construction algorithm that segments the input dataset based on sampling rate and movement characteristics and then infers the respective network layers. To fuse the semantic and geometric network layer into a NOI, we introduce a semantics-based algorithm that takes position samples (check-ins) to create network hubs. A detailed experimental evaluation uses two real-world datasets of geocoded tweets and discusses the NOI construction results in terms of quality and significance.

The remainder of this paper is organized as follows. Section 2 reviews related work on spatiotemporal inference techniques. Sections 3 and 4 present our algorithms for trajectory segmentation and re-association to build the NOI in a layered fashion. In Section 5, we evaluate the quality of the NOI construction method. Finally, Section 6 concludes the paper and outlines future research directions.

2 Related Work

Various approaches have been proposed for using user-generated geospatial content to extract useful knowledge, such as identifying travel sequences, interesting routes or

socio-economic patterns. In the following, we present a review of the literature using a categorization of the approaches according to the type of problem solved.

Several methods focus on *sub-sequence extraction (routes) from moving object trajectories* by mining spatiotemporal movement patterns in tracking data. Kisilevich et al. [3] present an automatic approach for mining semantically annotated travel sequences using geo-tagged photos by searching for sequence patterns of any length. In [4], Chen et al. extract important routes between two locations by observing the traveling behaviors of many users. Although, they mine a transfer network of important routes, they accept that the distance between any two consecutive points in a trajectory does not exceed $100m$, which becomes unrealistic. Zheng et al. [5] use online photos from Flickr and Panoramio to analyze people's travel patterns at a tour destination. They extract important routes, but no transportation network. Asakura et al. [6] investigate the topological characteristics of travel data, but they focus on identifying a simple index of clustering tourist's behavior. Mckercher and Lau [7] identify styles of tourists and movement patterns within an urban destination. Our approach analyzes, both, traffic patterns and topological characteristics of travel routes, while most existing work focuses on traffic patterns only. Choudhury et. al [8] explore the construction of travel itineraries from geo-tagged photos. In contrast, in this work an itinerary is defined as a spatiotemporal movement trajectory of much finer granularity.

There also exist various methods based on *trajectory clustering*. The majority of the proposed algorithms such as k-means [9], BIRCH [10] and DBSCAN [11] work strictly with point data and do not take the temporal aspect into consideration. Several approaches match some sequences by allowing some elements to be unmatched as in the Longest Common Sub Sequence (LCSS) similarity measure [12]. However, our goal in this work is rather to apply a trajectory clustering approach and also take into consideration the temporal aspect of the data. Similarity measures for trajectories that take the time and derived parameters, such as speed and direction, into account have been proposed in [13]. This approach is close to ours with respect to the examined aspects of temporal dimension, however, our method applies clustering techniques in order to infer the connectivity of a NOI. In a previous work [14], we derived a connected road network embedded in vehicle trajectories, while in [15] we inferred a hierarchical road network based on different movement types. The current approach differs in that it deals with uncertain social media check-in data by taking into account the spatial as well as the temporal dimension to derive a NOI.

Characterized by its spatial and temporal dimension, geocoded tweets can be regarded as one kind of spatiotemporal data, which also connects this study to the knowledge extraction-based techniques of the spatiotemporal data mining domain. Crandall et. al [16] investigate ways to organize a large collection ($\sim$ 35 million) of geo-tagged photos and determine important locations of photos, such as cities, landmarks or sites, from visual, textual and temporal features. Kalogerakis et. al [17] estimate the geolocations of a sequence of photos. Similarly, Rattenbury et. al [18] and Yanai et. al [19] analyzed the spatiotemporal distribution of photo tags to reveal the inter-relation between word concepts (photo tags), geographical locations and events. Girardin et al. [20] extract the presence and movements of tourists from cell phone network data and the geo-referenced photos they generate. Similarly, [21] proposes a clustering algorithm of

places and events using collections of geo-tagged photos. These approaches efficiently deliver focal spatial data extractions from diverse data sources, while the aim of this work is to also extract *how this data is connected (links)*. In [22], Kling studies urban dynamics based on user generated data from Twitter and Foursquare using a probabilistic model. However, these dynamics have not been translated to a (transportation) graph structure.

All these works target the extraction of some kind of knowledge and patterns from photos or geo-referenced sources with textual and spatiotemporal metadata, while we focus on mining transportation and mobility patterns from check-in data, such as geocoded tweets from Twitter.

Overall, what sets this work aside is that *social media data is used as a tracking data source*. We use it not only to extract features or knowledge patterns of human activities, but a complete Network of Interest.

3 NOI Layer Construction

As explained in Section 1, our goal is to extract a Network of Interestthat captures interesting information about user movement behaviors based on social media tracking data. User check-in data are tuples of the form $U = \langle u, x, y, t \rangle$, denoting that the user u was at location (x, y) at time t. These data are organized into trajectories, which represent the sequence of locations a user has visited. Typically, multiple trajectories are produced for each user by splitting the whole sequence of check-ins, e.g., on a daily basis. Hence, each resulting trajectory is an ordered list of spatiotemporal points $T = \{p_0, \ldots, p_n\}$ with $p_i = \langle x_i, y_i, t_i \rangle$ and $x_i, y_i \in R, t_i \in R^+$ for $i = 0, 1, \ldots, n$ and $t_0 < t_1 < t_2 < \ldots < t_n$.

The goal is to construct a Network of Interest that reveals the *movement behavior* of users. This Network of Interest is a directed graph $G = (V, E)$, where the vertices V indicate important locations and the edges E important links between them according to observed user movements. In particular, we are interested in two aspects of the Network of Interest. A *geometric NOI aspect* provides a representation of how users actually move across various locations, thus preserving the actual geometry of the movement, while a *semantic NOI aspect* represents the qualitative aspect of the network by identifying significant locations and links between them. In our approach, we treat these two aspects as different layers of the same Network of Interest. In the following, we describe the steps for constructing these layers and fusing them to produce the final Network of Interest.

3.1 Segmentation of Trajectories

Behavioral trajectories, as in our case derived from geocoded tweets, contain data to construct both the geometric and the semantic layer of a Network of Interest. Conceptually, users tweet when they stroll around in the city as well as when they commute in the morning. While all these tweets will result in behavioral trajectories, *some of them depict actual movement paths*, while others simply are tweets sent throughout the day. In what follows, we try to separate our input data into two subsets and to extract the trajectories corresponding to the respective layer.

A main challenge when inferring a movement network from check-in data is that this data is very heterogeneous in terms of their sampling rate, i.e., often being very sparse. However, even the sparse subsets of the data are helpful in identifying significant locations, whereas the denser subsets can be used to capture more fine grained patterns of user movement.

For this purpose, we analyze the trajectories and group them into subsets with different temporal characteristics. In our approach, we treat these two aspects by applying a (i) *mean speed* threshold to capture the user movement under an urban transportation mode and by applying (ii) a *sampling rate* threshold to identify "abstract" and "concrete" movement. This allows us to treat each subset separately later on in the network construction phase. The "abstract" type of movement corresponds to the *semantic NOI aspect* and the "concrete" corresponds to the *geometric NOI aspect*.

Users with frequent check-ins, i.e., a high sampling rate, provide us with the means to derive a geometric NOI layer, while low sampling rates only allow us to reason about abstract movement, i.e., derive a semantic NOI layer.

Notice that typically the same individual, within one daily trajectory may have recorded their data using different sampling rates. In this case, the trajectory needs to be segmented according to the frequency of user position samples. A simple process for achieving this separation is the following. First, a duration and a speed (length divided by duration) is recorded for each segment of a trajectory. Each segment is assigned a corresponding duration type of movement. Focusing on urban transportation, we use a mean speed to filter out trajectories and then the duration between samples to determine "abstract" and "concrete" movement. Figure 1a shows the trajectories classified to different sampling rates using the example of geocoded tweets for London. Using a heatmap coloring schema, concrete and abstract movements are shown in blue and red, respectively.

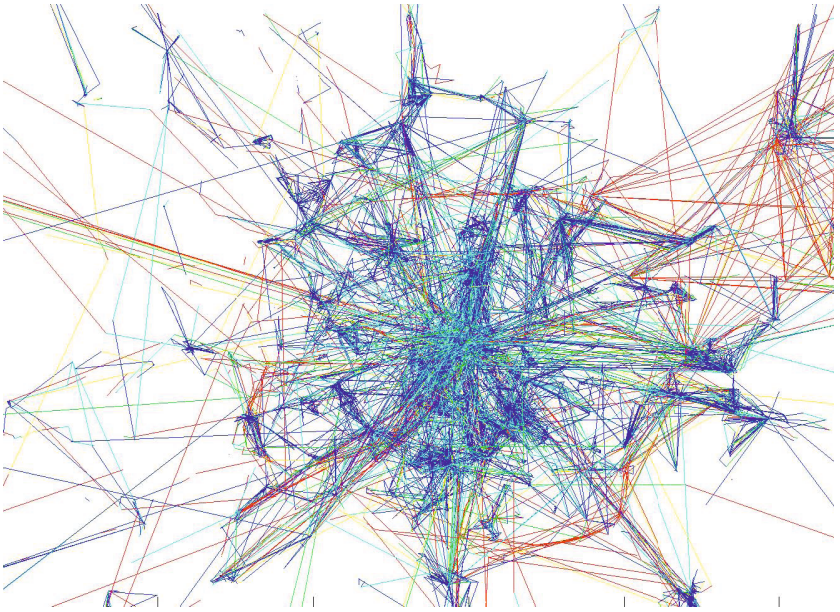
The process is outlined in Algorithm 1. For each line segment L_j of each trajectory T, we compute a duration and a mean speed value (Algorithm 1, Lines 6-7), and the segment is then assigned to the corresponding segmented set of trajectories T_G, T_S according to the min and max time interval (Lines 9-13). The algorithm produces segmented sets of trajectories (Lines 10 and 13) based on the corresponding time interval attributes.

3.2 Geometric Layer Construction

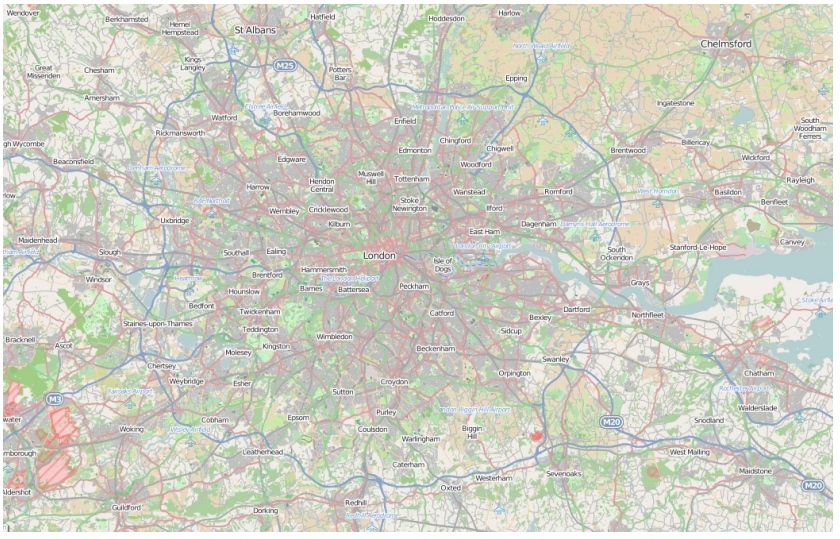
To construct the geometric NOI layer we use frequently sampled trajectories. The sampling rate threshold was established through experimentation. In the examples of Section 5, the sampling rate threshold was set to $5min$. I.e., for the construction of the geometric layer the duration in between position samples of trajectory dataset is less than $5min$ (cf. Table 1), approximately covering 57% of the original tweets collection.

The geometric NOI layer construction approach follows a modified map construction approach (e.g., [14,15]) by (i) initially clustering position samples to derive network nodes, (ii) linking nodes by using the trajectory data and (iii) refining the link geometry.

To derive network nodes we employ the DBSCAN clustering algorithm [11] using a distance threshold and a minimum number of samples threshold parameter. We revisit the segmented trajectories to identify how the network nodes are connected by



(a) Twitter trajectories("slow": blue, "fast": red)



(b) Respective OSM network

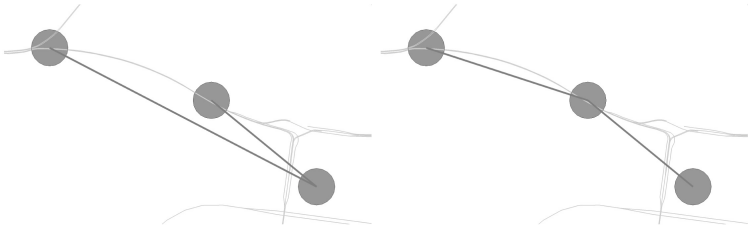
Fig. 1. Twitter Trajectories and OSM Network London (bounding box: [51.18N, 0.85W],[51.80N, 0.86E])

Algorithm 1. Segmentation of Trajectories

Input: A set of trajectories T
Output: Two sets of segmented trajectories T_G, T_S

begin
  /***Trajectories segmentation according to time intervals***/
  $V_{max} \triangleright$ maximum mean speed
  foreach $(T_i \in T)$ **do**
    foreach $(L_j \in T_i)$ **do**
      $\overline{t}(L_j) \leftarrow \delta t(P[i-1], P[i]) \triangleright$ Time interval
      $\overline{v}(L_j) \leftarrow \frac{\delta x(P[i-1],P[i])}{\delta t(P[i-1],P[i])} \triangleright$ Mean speed
      if $\overline{v}(L_j) \leq V_{max}$ **then**
        if $\overline{t}(L_j) \leq T_{min}$ **then**
          $T_G \leftarrow L_j$
        end
        else if $\overline{t}(L_j) \geq T_{min}$ *and* $\overline{t}(L_j) \leq T_{max}$ **then**
          $T_S \leftarrow L_j$
        end
      end
    end
  end
end

creating links. The links represent clustered trajectories as two nodes can be connected by different trajectories. For each link (i) a *weight* is derived representing the number of the trajectories comprising the link and also (ii) a *length* representing the Euclidean distance between the nodes that constitute the link. In addition to this, we apply a reduction step to simplify the constructed network. The intuition is that due to varying sampling rates, links between nodes might exhibit redundancy. This reduction step eliminates redundant links by substituting longer links with links of more detailed geometries. We reconstruct links of longer duration by using links of shorter duration if their geometries are similar. We achieve this by using the degree of constructed nodes. Starting with nodes of a higher degree of incoming links, i.e., significant nodes, for such a node, we sort all incident links based on descending duration order. We then reconstruct those, which temporally and spatially cover other links that can be reached in less time. Figure 2a gives an example by showing in dark gray links before reduction, and in light gray a portion of the underlying OSM transportation network. Figure 2b shows then in dark gray the resulting links after applying the reduction step. Part of the larger geometry has been substituted with a more detailed geometry.



(a) before reduction **(b)** after reduction

Fig. 2. Network Reduction Example - constructed network is shown in dark gray and the road network in light gray

3.3 Semantic Layer Construction

To construct the Semantic NOI layer, we rely on trajectories exhibiting low sampling rates (using approximately 19% of the original tweets collection), i.e., potentially cover large distances in between position samples making it difficult to reconstruct the actual movement (cf. Table 1). By initially applying the DBSCAN clustering algorithm (see Table 1 for parameter details), we extract a set of nodes that correspond to the *hubs* of the semantic layer. Performing a linear scan of the trajectories reveals the respective portions that connect the sets of nodes. For each link sample (i) a *weight* is derived representing the number of the trajectories comprising a link. At this step, we do not apply any reduction method as the geometries of the semantic layer are less accurate. Overall, this layer allows us to extract a network with less spatial accuracy but of greater semantic value.

4 NOI Construction and Layer Fusion

The final part of the Network of Interest construction process consists of (i) the extraction of hubs, i.e., significant locations that user frequently visits, and (ii) the fusion of the layers, i.e., the geometric and the semantic layer to produce the integrated network.

4.1 Network Hubs

Hubs are POIs that users frequently depart from and arrive at. In particular, specific indicators for hubs are (i) number of constituting position samples, (ii) stemming from many different users, (iii) over extended periods of time.

The Network Hubs Inference algorithm takes as input the *entire trajectory dataset* used in geometric and semantic layer construction (Algorithm 2, Line 9) and determines the k-NNs of each position sample (Line 12), which are subsequently filtered according to the number of users and the period of time covered (Lines 13-15). On these filtered position samples, we apply the DBSCAN clustering algorithm using a distance threshold and a minimum number of samples (Line 16). The centroids of the resulting clusters are the candidate hubs (Line 17). A final filtering step is applied as follows. For each

candidate hub, we also record two properties. A *weight* for the hub is derived as the total number of nodes the hub was derived from, i.e., the size of the corresponding cluster. In addition, we record the *degree* of each hub, i.e., the number of incoming and outgoing edges of the cluster. A candidate hub is included in the output if both the following two conditions hold: (a) both the in-degree and out-degree are above a specified threshold and (b) the in-degree and out-degree do not differ significantly (threshold determined by experimentation). These conditions are used to ensure that the identified hubs correspond to places where a sufficiently large number of users frequently depart from and arrive at (Lines 23-24).

Algorithm 2. Hub Inference

Input: A set of segmented trajectories T_G, T_S
Output: Network Hubs

1 **begin**
2 /***Clustering position samples of segmented trajectories to compute network hubs***/
3 $H^* \leftarrow \emptyset$ ▷ Candidate Hubs
4 $H \leftarrow \emptyset$ ▷ Hubs
5 d_{max} ▷ proximity threshold
6 u_{min} ▷ min. number of users
7 h_{min} ▷ min. number of time periods
8 $deg_{in}, deg_{out}, deg_{min}, \epsilon$
9 ▷ position samples from combined trajectories
10 $P \leftarrow \text{UNION}(T_G, T_S)$
11 ▷ Samples $\rightarrow$ Hubs
12 **foreach** $(P[i])$ **do**
13 $\nu_i \leftarrow \text{FINDNN}(P[i], d_{max})$
14 $u_p \leftarrow \text{COUNTUSERS}(\nu_i)$
15 $h_p \leftarrow \text{COUNTHOURS}(\nu_i)$
16 **if** $(u_p \geq u_{min})$ *and* $(h_p \geq h_{min})$ **then**
17 $C \leftarrow \text{DBSCAN}(\nu_i, d_{max})$ ▷ Clusters
18 $H^* \leftarrow \text{CENTROID}(C)$ ▷ Hub candidates
19 **end**
20 **end**
21 **foreach** $H^*[i]$ **do**
22 $deg_{in} \leftarrow \text{GETINDEG}(H^*[i])$
23 $deg_{out} \leftarrow \text{GETOUTDEG}(H^*[i])$
24 **if** $deg_{in} \geq deg_{min}$ *and* $deg_{out} \geq deg_{min}$ *and* $\left|\frac{deg_{in}}{deg_{out}} - 1\right| \leq \epsilon$ **then**
25 $H \leftarrow H^*[i]$
26 **end**
27 **end**
28 **end**

4.2 Layer Fusion

The final part of the process comprises the fusion of the geometric and semantic NOI layers. We construct the NOI by starting with the semantic layer and merging the geometric layer onto it. The intuition for this is that the semantic layer corresponds to a geometrically abstract but semantically richer user movement that contains relevant transportation hubs. The geometric layer corresponds to a less semantic but more accurate depiction of movement, i.e., fills in the gaps of the semantic layer. The fusion of these layers should result in a comprehensive movement network.

The fusion task involves (i) finding hub correspondences among the different network layers and (ii) introducing new links to the semantic layer for the uncommon portions of the NOI.

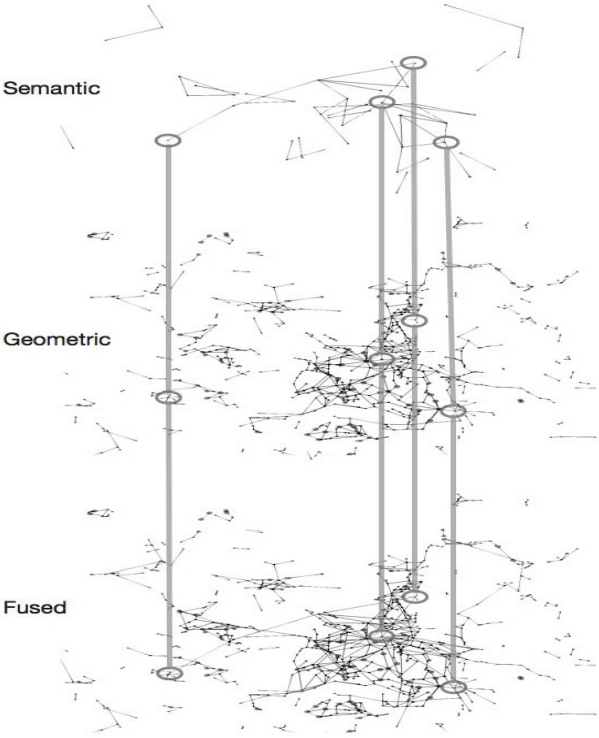


Fig. 3. London - Fused Network

Using, both, layers and the hubs, we try to identify common nodes by spatial proximity (Algorithm 3, Lines 11-13). Any node from the geometric layer that has not been introduced yet since it is not connected to the semantic layer will be added (Lines 22-23). The next step involves introducing new links for uncommon portions of the layered

Algorithm 3. NOI Fusion

Input: Networks to be conflated S, G
Output: Network of Interest

```
1  begin
2      /*Network layers fusion to extract the final map*/
3      ▷ edges and nodes of Semantic and Geometric layers
4      E_S ← EDGES(S), N_S ← NODES(S)
5      E_G ← EDGES(G), N_G ← NODES(G)
6      H ▷ Hubs
7      H_G ▷ hubs ∩ geometric nodes
8      H_S ▷ hubs ∩ semantic nodes
9      H_O ▷ H − H_G − H_S
10     ▷ Node alignment
11     foreach H[i] do
12         ▷ finding Nearest Neighbors H_G ← (H[i], NN(H[i], N_G))
13         H_S ← (H[i], NN(H[i], N_S))
14     end
15     ▷ Node alignment
16     foreach H_G[i] do
17         H_O ← (H_G[i], 1-NN(H_G[i], H_S))
18         ▷ Node insertion to semantic layer
19         foreach (H_G[i] ∉ H_O) do
20             E_i = ON(E_S, H_G[i])
21             if E_i ≠ NULL then
22                 H_S.add(H_G[i])
23                 E_S.delete(E_i)
24             end
25         end
26         ▷ Link insertion
27         foreach (H_G[i] ∉ H_S) do
28             H_S.add(H_G[i]) ▷ remaining nodes
29             foreach (E_G[i] ∉ E_S) do
30                 E_S.add(E_G[i]) ▷ remaining links
31             end
32         end
33     end
34 end
```

network. Here links of the geometric layer are introduced by adding them to the semantic layer (Lines 28-30). Typically this accounts for the cases of adding complete (local) network portions.

A result of applying this conflation algorithm to network layers is shown in Figure 3. Indicated are the circled hub correspondences between the semantic, the geometric layer, and the resulting fused Network of Interest

5 Experimental Evaluation

An assessment of the quality of a Network of Interest is a challenging task as there is no ground-truth data. In the case of map-construction algorithms, an existing road network can be used. However, a NOI represents a geosemantic construct containing aspects of both, regular transportation networks (roads, public transport, etc), but also the overall movement sentiment of users in a city. For the following evaluation, we will use a combination of existing POI datasets and (public) transportation networks to assess the constructed NOIs. Before giving details of the experimental results and constructed NOIs, we first describe the characteristics of the datasets used and our overall evaluation methodology.

5.1 Experimental Setup

We conduct experiments on two real-world datasets comprising geocoded tweets retrieved for London and New York City over a period of 60 days using the Twitter Public Stream API. Data from London covers the period of December 2012 to January 2013. The New York as collected from November 2013 to December 2013. To focus on trajectories of active users, we kept only the trajectories of the top 200 most active users with respect to geotweets for each city. Moreover, we only consider trajectories that consist of at least 5 geotweets. Figure 1a visualizes the movements of 200 Twitter users during the course of a single day in London. Notice that some very prominent areas, such as highways, can be distinguished visually even before any processing of the data takes place.

Through experimentation, we established the parameters for the various steps of the algorithm as summarized in Table 1. To compare the generated network, we consider as ground-truth data the corresponding public transportation network obtained from OSM [23]. What follows is a brief description of the trajectories collected from the geocoded tweets, as well as the networks obtained from OSM.

In London, the actual public transportation network consists of 27,021 links (edges) and 47,575 nodes (vertices) and has a length of 21,287km. It covers an area of 420km $\times$ 118km including the metropolitan area of London. The geocoded tweets cover a great portion of this network, specifically an area of 365km $\times$ 104km, and have a total combined length of 256,400km (Figure 1a). The dataset consists of 463 trajectories with a median length of 7.4km. The median sampling rate, i.e., rate at which a user geotweets, is 12min, while the median speed is 37km/h.

For New York the actual public transportation network consists of 84,367 links and 75,070 nodes and has a length of 9,846km. It covers an area of 105km $\times$ 85km. The geocoded tweets consist of 37,962 trajectories, with a median length of 2.9km and total length of 214,090km, covering an area of 92km $\times$ 74km largely overlapping with the public transportation network. The median sampling rate is 8min, while the median speed is 22km/h.

Table 1. Parameter Summary

Algorithm	Value
Segmentation of Trajectories	
Mean Speed	10km/h
Time Interval	5, 60min
Geometric NOI	
Distance Threshold	100m
Minimum Number of Samples	2
Semantic NOI	
Distance Threshold	300m
Minimum Number of Samples	2
Extraction of Hubs	
Minimum Number of Samples	10
Minimum Number of Users	2
Minimum Number of Time Periods	10
Distance Threshold	300m
Layer Fusion	
Distance Threshold	50m

5.2 Visual Comparison

A first and quick overview of the quality of the inferred Network of Interest can be obtained by *visual inspection*, i.e., by comparing it to the ground-truth public transportation network and looking for similarities and differences.

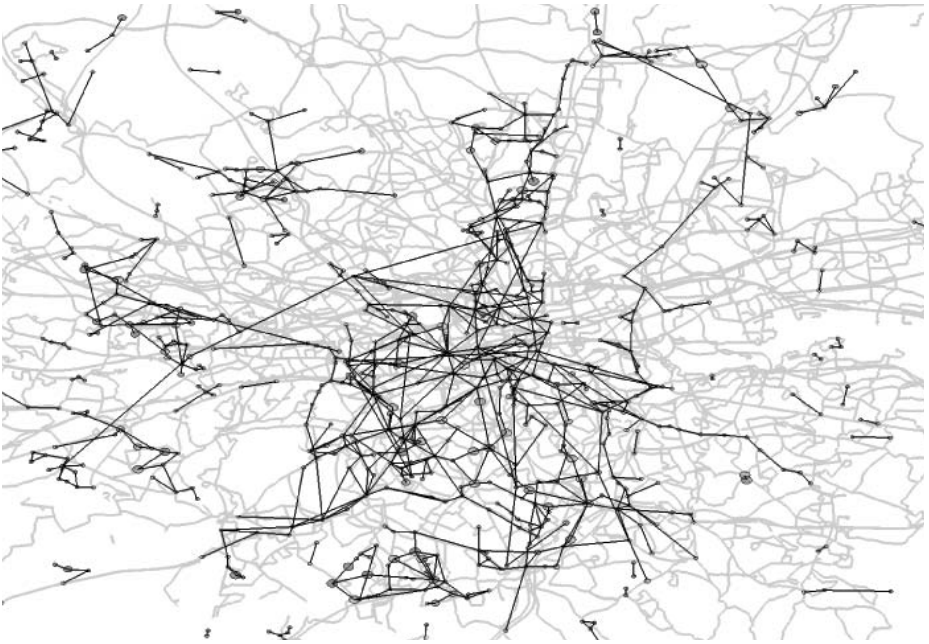
Figure 4 visualizes the NOIs of the cities of London (Figure 4a) and New York (Figure 4b). In each case, the constructed network is visualized using black lines, while the ground-truth network is shown using light gray lines. As evident, especially for the case of New York, the constructed NOI lines up with the transportation network and identifies major hubs.

5.3 Quantitative Evaluation

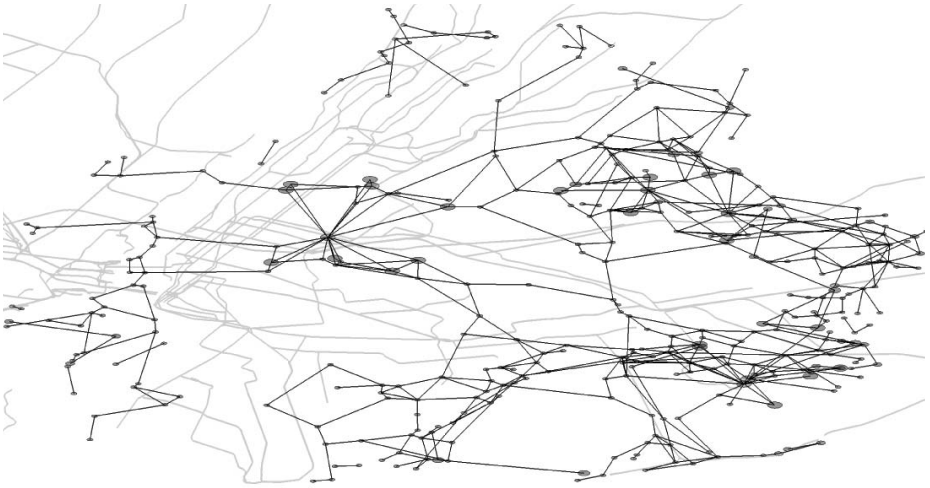
For a more systematic and quantitative assessment of NOIs, we devise two means, (i) comparing the constructed NOI to the geometry of a respective transportation network and (ii) comparing the nodes of our NOI with a POI dataset to discover semantics in terms of their type. This approach allows us to assess the similarity with respect to the ground-truth network and to draw conclusions not only with respect to the spatial accuracy of the result, but also the semantics of the nodes.

To *compare networks* we select all the nodes of the constructed network and identify corresponding nodes in the ground-truth network by means of nearest-neighbor queries. Using the OSM public transport data, we select for every hub of the Network of Interest the nearest node in the OSM data. If the inferred nodes are close to the actual transportation network nodes, then the constructed NOI closely relates to the transportation network.

To discover the *type of transportation* a hub represents, e.g., bus, metro, tram and railway, we again use OSM data. We apply reverse geocoding (identify POIs based on



(a) London (bounding box: [50.60N, 0.50W],[52.00N, 1.25E])



(b) New York (bounding box: [40.54N, 74.10W],[40.92N, 73.70W])

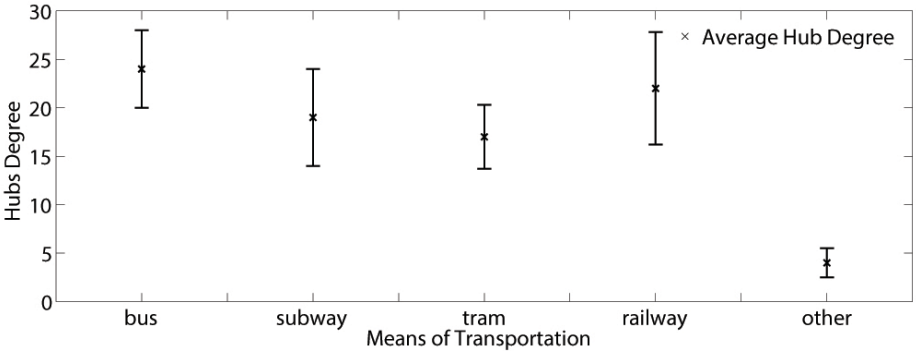
Fig. 4. Networks of Interest

coordinates) to relate OSM POIs to NOI locations. This then allows us to identify public transportation nodes in our generated Network of Interest. The results are summarized in Figure 5, which shows the degree of a node, i.e., the number of incoming and outgoing links. In this case, we use the degree as an indicator for the importance of the node and the fact that high-degree nodes were identified as transportation nodes allows us to reason about the type of network we constructed. Identified transportation nodes (i.e. bus, metro, etc) have higher degrees (> 20) when compared to *other* nodes with lower degree (< 5).

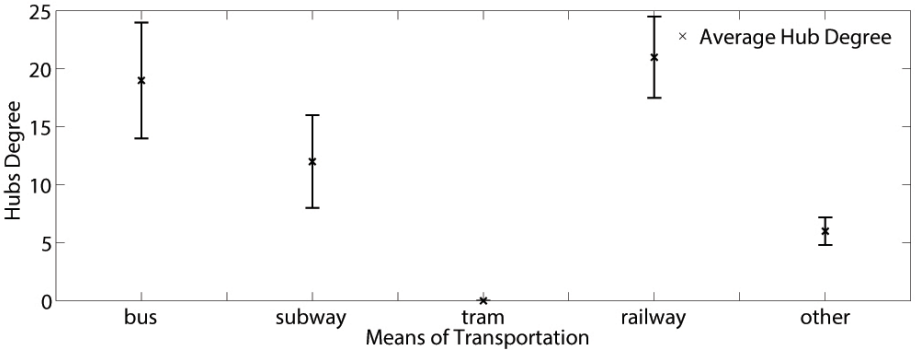
In this experimentation, (i) nearest-neighbor queries evaluate the spatial accuracy of the NOI, while (ii) the reverse geocoding assesses the semantics of the hubs. The higher

Table 2. Evaluation Summary

	Nearest Neighbor Statistics			Reverse Geocoding Statistics		
	Found	**Total**	**Ratio %**	**Found**	**Total**	**Ratio %**
London	1389	1562	89	964	1562	62
New York	1423	1649	86	873	1649	53



(a) London



(b) New York

Fig. 5. Hubs Statistics

the number of correctly constructed nodes, the higher also the quality of the network. As shown in Table 2, transportation nodes are inferred with high accuracy. 89% of the extracted hubs in London and 86% in New York are identified as transportation nodes in the OSM ground-truth network. In the case of the reverse geocoding test, the ratios are a bit lower due to the fact that the reverse geocoding service returns only POIs that are located exactly or very closely to specific coordinates.

An overall sentiment of our experimentation could be that the network construction process results in a Network of Interest that *captures certain aspects of a public transportation network*. A core problem in such experimentation is that using social media as a tracking data source to construct a network has the inherent challenge that no actual ground-truth data is available to assess the quality of the result. Using in our case a public transportation network allows us to show some similarities, however, the constructed NOI could not be completely mapped (explained) by it as it represents a more complex network whose characteristics cannot be captured by a single existing network dataset. These concerns are also issues we want to address in future work.

6 Conclusions

Social media applications and their data have been used in a wide range of data mining applications. However, to the best of our knowledge this work is the first to construct a geosemantic Network of Interest using social media as a tracking data source. The NOI construction algorithm is based on segmenting geocoded tweets and constructing two separate network layers. A geometric and a semantic layer of a NOI are derived and using network hubs, these layers are then fused to generate a Network of Interest. Performing an experimental evaluation using two large-scale datasets, the algorithm produces NOIs of considerable accuracy, which identify important transportation hubs and capture portions of the respective public transport networks.

The directions for future work are to refine the NOI construction process and scaling the algorithms and to use it for larger datasets and more complex NOIs. Here, we will also have the opportunity to identify temporal aspects of the NOIs, e.g., transportation routes to and from the city, temporal variations, as well as characteristics of the NOI graph itself (connected components). We are also in the process of applying the proposed methods to mobile phone tracking data, a dataset that is "in between" GPS tracking data and check-in data in terms of positional accuracy and sampling rate.

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