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# Self-Supervised Representation Learning for Geographical Data - A Systematic Literature Review Supplementary Material

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## Introduction

This document contains supplementary material for the systematic literature review presented in [1]. Each of the following sections contains supplementary material corresponding to the section with the same number and/or title in the original article.

### *3.3. Selection Criteria*

The following is the complete list of the 108 articles reviewed in alphabetical order: [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [101], [102], [103], [104], [105], [106], [107], [108], [109].

### *4.1. What types of representations were learnt?*

In this section, for each individual data type, we state the number of articles that considered the problem of learning representations of that type. For each type, we also list the corresponding articles and describe the specific data they used.

#### Location Representations

A total of 10 articles considered the problem of learning representations of locations (see Table S1 for details).

**Table S 1.** Location representations

| Article | Location |
|---|---|
| [16] | buses travelling in a street network |
| [67] [14] | telecommunication base stations that mobile devices connect to |
| [61] | WiFi hotspots that mobile devices connect to |
| [90] | geotagged images in Flickr, an image sharing platform |
| [64] | posts on Twitter, a social media platform |
| [69] | POIs |
| [85] | ‘locations’, which may be POIs |
| [39] | customer home locations |
| [91] | POIs and geotagged images in Flickr |

### Individual POI Representations

A total of 31 articles considered the problem of learning representations of individual POIs. Table S2 displays some of the most frequently used data sources. In some cases, individual POIs are modelled as a tuple of multiple features. [44] modelled individual POIs as a tuple of an individual POI plus a user. Consequently, personalised individual POI representations were learnt. [42] modelled individual POIs as a tuple of an individual POI plus a time. Consequently, temporal individual POI representations were learnt. The following works also considered the problem of learning representations of individual POIs: [8], [13], [21], [22], [29], [32], [33], [57], [68], [86], [99] and [100].

**Table S 2.** Individual POI representations

| Article | POI source |
|---|---|
| [60]<br>[46]<br>[101] | the LBSNs Foursquare and Gowalla |
| [87]<br>[79]<br>[28] | the review website Yelp |
| [7]<br>[42]<br>[70] | the Chinese review website dianping.com |
| [34] | the web map service Baidu Maps |
| [104]<br>[106] | the New York City data portal NYC Open Data |
| [84]<br>[18]<br>[2]<br>[5]<br>[40] | the LBSN BrightKite |
| [55] | Plancast, an event-based social network |

### POI Type Representations

A total of 9 articles considered the problem of learning representations of POI types. The sources of POIs are provided in Table S3. Note that the web service Amap mentioned in this table is also known as Gaode in Chinese.

**Table S 3.** POI type representations

| Article | POI source |
|---|---|
| [46] | the LBSNs Foursquare and Gowalla |
| [35] | the web map service Baidu |
| [108]<br>[31] | the web map service Amap |
| [19] | a real estate website |
| [85] | the Facebook social network place graph |
| [82]<br>[48] | the review website Yelp |
| [58] | the Ordnance Survey |

### Region Representations

A total of 18 articles considered the problem of learning representations of regions. In many articles, the regions correspond to grid cells of various sizes (see Table S4 for details). In the article [36], a region is modelled as a tuple of a cell plus a time. Hence, spatial-temporal representation is learnt.

**Table S 4.** Representations of regions defined as grid cells

| Article | Region |
|---|---|
| [37] | 0.30km × 0.80km<br>0.22km × 0.28km |
| [47] | 0.5km × 0.5km |
| [95] | 0.3km × 0.3km |
| [50] | 0.3km × 0.3km |
| [63] | 0.5km × 0.5km<br>1.0km × 1.0km<br>10.0km × 10.0km |
| [108] | 4.0km × 4.0km<br>1.0km × 1.0km<br>0.25km × 0.25km<br>0.0625km × 0.0625km |
| [36] | 10.0km × 10.0km |

In other articles, the regions correspond to less regular shapes than rectangular cells (see Table S5 for details). A structural region in [77] is composed of a set of spatially connected road segments, serving as some traffic role, e.g., overpass and crossing. A functional zone consists of multiple structural regions, providing some kind of traffic functionality, e.g. shopping areas and transportation hubs. The grid cells in [58] are of sizes 0.2km × 0.2km, 0.5km × 0.5km and 1.0km × 1.0km.

**Table S 5.** Representations of regions defined as less regular shapes

| Article | Region |
|---|---|
| [110] | residential communities or regions |
| [42] | urban communities consisting of one or more residential complexes |
| [85] | places, e.g. a park |
| [17] | cities |
| [43] | populated places in the geographical database Geonames |
| [77] | functional zones and structural regions |
| [24]<br>[96] | circular regions centred at a given point |
| [70] | residential communities |
| [15] | Neighborhood Statistical Areas defined by the USA government |
| [58] | both UK census units and grid cells |

Time Representations

A total of 7 articles considered the problem of learning representations of time (see Table S6 for details).

User Representations

A total of 27 articles considered the problem of learning representations of users (see Table S7 for details).

**Table S 6.** Time representations

| Article | Time window |
|---|---|
| [36] | a month of the year |
| [99]<br>[42] | a day of the week |
| [64] | an hour of the day |
| [71] | an hour of each day of the week |
| [95]<br>[50] | the total time duration divided by the number of time windows, which is a hyperparameter |

Activity Representations

A total of 10 articles considered the problem of learning representations of activities. In [59], [78], [10], [26], [51] and [83] the activities correspond POI checkins in a LBSN. In many cases, activities are modelled as tuples of multiple features. For example, in [59] a checkin equals a tuple of the individual POI, the region containing this POI, the user who performed the checkin and the time the checkin happened. Similarly, in [83] a checkin equals a tuple of the individual POI, the type of POI and the time the checkin happened. In [93] and [76] the activities correspond to posting on the social media platform Twitter. In both of these articles, the activities are modelled as a tuple of three features equalling the text, time and location of the post. In [94] the activities correspond to both checkins to POIs in a LBSN and posting on the social media platform Twitter. In [16] the activities correspond to a bus being en route, stopped at a bus stop, stopped at a traffic signal and stopped at other stops.

Event Representations

A total of 4 articles considered the problem of learning representations of events. In [53] representations of traffic accidents were learnt. In [45] representations of time and weather condition tuples were learnt; that is, a temporal weather representation. In [71] representations of event types were learnt. In this article, an event is modelled as a location and time tuple. In [15] representations of crime types were learnt.

Location Trajectory Representations

A total of 15 articles considered the problem of learning representations of location trajectories (see Table S8 for details).

Activity Trajectory Representations

A total of 7 articles considered the problem of learning representations of activity trajectories. In all articles, the trajectories correspond to trajectories of POI checkins in a LBSN [6], [26], [50], [84], [95], [105], [107].

Text Representations

A total of 12 articles considered the problem of learning representations of texts (see Table S9 for details).

Street Segment & Intersection Representations

A total of 6 articles, including [25], [73], [27], [38], [77] and [109], considered the problem of learning representations of street network segments.

A total of 2 articles, including [97] and [73], considered the problem of learning representations of street network intersections.

**Table S 7.** User representations

| Article | User |
|---|---|
| [87] [10] [60] [13] [22] [18] [32] [69] [79] [33] [68] [21] [86] [80] [100] [2] [28] [83] [8] [40] | a user of a LBSN such as Foursquare and Gowalla |
| [64] [103] [66] | a Twitter user |
| [14] | a mobile phone user |
| [20] [75] | a vehicle driver |
| [44] | a public transport user |
| [23] | a customer of home delivery |
| [17] | a tourist who travels to different cities |

Other Representations

Finally, a total of 6 articles considered the problem of learning representations of a data type that does not correspond to any element in the proposed taxonomy. In [19] representations of houses were learnt. In [56] representations of knowledge graph entities and relations were learnt where these entities and relations model geographical knowledge. In [106] representations of bike sharing stations were learnt. In [109] representations of car parks were learnt. In [45] representations of bike stations and time tuples were learnt; that is, temporal bike station representation. Finally, in [49] representations of trajectories of transportation hubs, in a multi-modal transportation network, were learnt.

4.2.1. SSRL Models Used

A total of 61 articles used a contrastive SSRL model. These articles are listed here in alphabetical order: [2], [3], [5], [6], [7], [9], [11], [12], [13], [15], [16], [17], [18], [19], [22], [23], [25], [27], [28], [30], [31], [34], [35], [38], [41], [43], [45], [48], [50], [51], [52], [54], [56], [59], [60], [61], [62], [64], [65], [66], [68], [71], [73], [75], [76], [78], [79], [80], [82], [84], [85], [86], [87], [93], [95], [97], [98], [99], [104], [107], [108].

A total of 19 articles used an autoencoder which is considered a pretext SSRL model. These articles are listed here in alphabetical order: [8], [110], [24], [37], [39], [42], [47], [50], [53], [55], [65], [70], [72], [74], [87], [88], [92], [95], [96].

A total of 32 articles used a pretext SSRL model other than an autoencoder. These articles are listed here in alphabetical order: [4], [14], [20], [21], [26], [29], [32], [33], [36],

**Table S 8.** Location trajectory representations

| Article | Trajectory |
|---|---|
| [25] [4] [11] [65] [74] [72] [52] [12] [102] [9] | a GPS trajectory |
| [54] [14] | a trajectory of telecommunication base station locations that mobile devices connect to |
| [92] | an origin-destination pair of metro stations |
| [88] | a trajectory of ship locations determined with the Automatic Identification System |
| [69] | a trajectory of individual POI locations |

**Table S 9.** Text representations

| Article | Text |
|---|---|
| [62] [89] [81] [98] | postal addresses |
| [85] | postal addresses and place names |
| [41] | general documents |
| [95] [50] | descriptions of POI check-ins in a LBSN |
| [79] | user reviews |
| [64] [3] [30] | Twitter posts (also known as tweets) |

[37], [40], [44], [45], [46], [49], [58], [63], [67], [69], [77], [81], [83], [89], [90], [91], [94], [100], [101], [102], [103], [106], [109].

Only 2 articles used a generative SSRL model: [2] and [105].

Finally, 4 articles used a method based on matrix factorization to learn representations: [10], [32], [57] and [69].

#### 4.2.2. Learning Representations Independently

A total of 26 articles learnt more than one data type representation in an independent manner (see Table S10 for details).

#### 4.2.3. Learning Representations Hierarchically

In total 18 articles learnt more than one data type representation in a hierarchical manner (see Table S11 for details).

### *4.3. What downstream problems or tasks are the learnt representations used to solve?*

In this section, for each data type, we review all articles where the applications in question use a single learnt representation of that type. We subsequently review all articles where the applications in question used more than one learnt representation.

**Table S 10.** Independently learnt representations

| Article | Representations |
| --- | --- |
| [87] [60] [22] [18] [32] [33] [21] [86] [100] [2] [28] [40] [103] [8] [13] | individual POIs and users in a LBSN |
| [79] | individual POIs, users and user reviews |
| [46] | individual POIs and POI types |
| [19] | houses and POI types |
| [16] | locations and activities |
| [56] | knowledge graph entities and relations |
| [73] | street network segments and intersections |
| [10] [83] | users and activities |
| [17] | users and regions |
| [71] | locations and times |
| [109] | street network segments and car parks |

Location Representations

Table S12 provides details about the types of downstream tasks supported by learnt location representations. Note that the financial fraud in [39] concerns predicting whether a customer will fail to make required payments in the future.

Individual POI Representations

Table S13 provides details about the types of downstream tasks supported by learnt representations of individual POIs.

POI Type Representations

Table S14 provides details about the types of downstream tasks supported by learnt representations of POI types.

Region Representations

Table S15 provides details about the types of downstream tasks supported by learnt region representations.

User Representations

Table S16 provides details about the types of downstream tasks supported by learnt user representations.

Activity Representations

Table S17 provides details about the types of downstream tasks supported by learnt activity representations.

**Table S 11.** Hierarchically learnt representations

| Article | Representations |
|---|---|
| [78] | individual POIs followed by users |
| [25] | street segments followed by location trajectories |
| [84] | individual POIs followed by activity trajectories |
| [14] | locations followed by location trajectories |
| [42] | individual POIs and times followed by regions |
| [85] | locations, names and addresses followed by places |
| [69] | locations followed by location trajectories and users |
| [95] [50] | regions, times and activities followed by activity trajectories |
| [64] | times, locations, texts and users followed by activities |
| [26] | activities followed by activity trajectories |
| [68] | users followed by individual POIs |
| [77] | street segments followed by structural regions and functional zones |
| [106] | individual POIs followed by bike share stations |
| [58] [108] | POI types followed by regions |
| [70] | individual POIs followed by regions |
| [15] | crime types followed by regions |
| [109] | street network segments followed by car parks |

Event Representations

[53] used representations of traffic accidents to predict traffic congestion. [71] used representations of event type to perform event recommendation. [93] detected events such as a protest or a disaster. [45] used representations of weather conditions and bike stations to predict bike sharing station demand.

Location Trajectory Representations

Table S18 provides details about the types of downstream tasks supported by learnt location trajectory representations.

Activity Trajectory Representations

Table S19 provides details about the types of downstream tasks supported by learnt activity trajectory representations.

Text Representations

Table S20 provides details about the types of downstream tasks supported by learnt text representations.

Street Intersection & Segment Representations

Table S21 provides details about the types of downstream tasks supported by learnt representations of street intersections and segments.

**Table S 12.** Downstream tasks supported by location representations

| Article | Downstream task |
|---|---|
| [67] [61] [91] | predicting the next location a user will visit |
| [91] [90] | geotagged photograph classification |
| [39] | financial fraud detection and customer segmentation |

**Table S 13.** Downstream tasks supported by representations individual POIs

| Article | Downstream task |
|---|---|
| [101] [5] [44] [57] [29] [55] [99] | POI recommendation |
| [7] [104] | POI type classification and POI clustering |
| [34] | POI search auto-completion |

Other Representations

In [45] representations of weather conditions and bike stations were used to predict bike sharing station demand. In [49] representations of trajectories of transportation hubs were used to perform trajectory recommendation.

Multiple Representations

In total, there were 44 articles where the applications in question used more than one learnt representation.

A total of 16 articles considered the application of POI recommendation in an LBSN. The majority of these works used representations of individual POIs and users [8], [22], [32], [33], [13], [18], [87], [28], [46], [78], [100], [103], [60] and [86]. [79] used representations of individual POIs, users and user reviews to recommend POIs. [84] used representations of individual POIs and POI checkin trajectories to recommend POIs. [17] used representations of users and regions to recommend travel destinations. This is distinct from POI recommendation because cities instead of POIs are recommended. [40] and [21] used representations of individual POIs and users to predict which users will visit which POIs and select the most influential users. [68] used representations of individual POIs and users to classify POI types.

A total of 5 articles considered the application of social link prediction or friend recommendation in an LBSN. All of them used representations of individual POIs and users [100], [103], [86], [60], [2].

[64] used representations of times, locations, texts, users and activities to determine the location of and classify posts on the Twitter social media platform. [85] used representations of locations, names, addresses and places to disambiguate place names. [83] used representations of users and activities to identify functional zones and predict crimes. [42] used representations of individual POIs, times and regions to identify thriving communities. [106] used representations of individual POIs and bike share stations to predict bike demand for both and new existing bike stations. [108] used representations of POI types and regions to retrieve regions given keywords, e.g. “Sports and Leisure Service”. [58] used representations of POI types and regions to delineate urban regions of uniform

**Table S 14.** Downstream tasks supported by representations POI types

| Article | Downstream task |
|---|---|
| [35] | estimating the proportional distributions of function types (i.e. functional distributions) of urban regions |
| [31] | determining urban functional regions |
| [82] | measuring POI type similarity |
| [48] | an analysis of different POI type representations within a given city plus an analysis of the same POI type representations between different cities |

**Table S 15.** Downstream tasks supported by region representations

| Article | Downstream task |
|---|---|
| [37] | house price prediction |
| [47] | air quality prediction |
| [63] | land-use classification |
| [36] | predicting climate features and the distribution of animal species |
| [110] | predicting the number of second-hand houses |
| [24] [96] | predicting the number of POI check-ins |

functional use. [19] used representations of houses and POI types to predict house prices. [95] and [50] used representations of regions, times, activities and activity trajectories to measure trajectory similarity. [77] used representations of street segments and regions to predict the next location, classify road types, predict destinations based on a partial trajectory and plan routes. [70] used representations of individual POIs and regions to predict user willingness to pay (ratio of a property price increase relative to the starting price) and predict community vibrancy (a measure of both the density and diversity of check-in activities). [15] used representations of crime types and regions to visually analyse crime data. [10] used representations of users and activities to classify POI types, classify user gender and measure user similarity. [26] used representations of activities and activity trajectories to classify activity trajectories with respect to the user that generated them. [16] used representations of locations and activities to detect anomalous trajectories and to classify activities and bus routes. [25] used representations of street segments and location trajectories to measure trajectory similarity and predict travel time and destination. [73] used representations of street network segments and intersections to classify street intersections and segments. They were also used to predict travel time. [109] used representations of street network segments and car parks to predict traffic volume and parking occupancy. [14] used representations of locations and location trajectories to analyse different locations, individuals and groups of people. [69] used representations of locations, location trajectories and users to link trajectories, i.e. identifying those trajectories that were generated by the same individual. [56] used representations of knowledge graph entities and relations to answer logic queries.

### *4.4. What machine learning models are used to solve these downstream problems?*

A total of 34 articles used supervised neural network models. These articles are listed here in alphabetical order: [16], [17], [18], [20], [26], [27], [30], [33], [35], [44], [45], [47], [49], [53], [54], [55], [61], [62], [63], [67], [73], [77], [80], [81], [84], [87], [89], [90], [91], [98], [102], [103], [105], [107].

**Table S 16.** Downstream tasks supported by user representations

| Article | Downstream task |
|---|---|
| [80] | POI recommendation |
| [66] | predicting the location of Twitter users |
| [20] | predicting the duration of a trip |
| [75] | clustering vehicle drivers |
| [23] | clustering of users to allow better routing of delivery vehicles |

**Table S 17.** Downstream tasks supported by activity representations

| Article | Downstream task |
|---|---|
| [59] | POI recommendation |
| [51] | predicting the keywords, location and time of an activity |
| [93] | event detection such as a protest or a disaster |
| [94] | predicting properties of an activity such as the time and location |

A total of 14 articles used supervised linear models. These articles are listed here in alphabetical order: [2], [110], [21], [24] [25], [25], [66], [72], [79], [96], [100], [101], [106], [109].

A total of 12 articles used traditional supervised models. These articles are listed here in alphabetical order: [10], [16], [19], [36], [37], [38], [39], [60], [68], [73], [83], [100].

A total of 3 articles used logistic regression models: [7], [38] and [93].

A total of 13 articles used unsupervised clustering models. These articles are listed here in alphabetical order: [4], [6], [7], [23], [31], [39], [58], [74], [75], [83], [88], [92], [93].

A total of 4 articles used visualisation models: [3], [14], [15], and [48].

A total of 32 articles used a distance measure in the representation space (e.g. Euclidean distance). These articles are listed here in alphabetical order: [2], [4], [9], [10], [11], [12], [15], [22], [25], [34], [41], [50], [51], [52], [56], [59], [60], [64], [65], [69], [71], [74], [78], [82], [83], [85], [86], [94], [95], [97], [104], [108].

Finally, a total of 7 articles used other model types. These articles are listed here in alphabetical order: [28], [29], [32], [42], [46], [57], [99].

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**Table S 18.** Downstream tasks supported by location trajectory representations

| Article | Downstream task |
|---|---|
| [11] [65] [52] [12] [4] | measuring location trajectory similarity |
| [74] | trajectory anomaly detection |
| [72] | scoring driving performances and detecting dangerous driving regions |
| [102] | predicting traffic flow/volume entering and leaving different regions |
| [92] | the analysis of mobility patterns |
| [9] [54] | predicting the next location in a trajectory |
| [4] [88] | trajectory clustering |

**Table S 19.** Downstream tasks supported by activity trajectory representations

| Article | Downstream task |
|---|---|
| [105] | trajectory recommendation |
| [6] | trajectory clustering |
| [107] | next location prediction and matching trajectories to corresponding users |


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**Table S 20.** Downstream tasks supported by text representations

| Article | Downstream task |
|---|---|
| [62] | address matching (mapping addresses to locations) |
| [89] | multinational address parsing |
| [81] | address location prediction |
| [98] | address matching and address segmentation |
| [41] | named-entity disambiguation by assigning similar embeddings to the same spatial locations or places |
| [3] | qualitative spatial-temporal analysis of social media posts |
| [30] | determining the locations of posts on Twitter |

**Table S 21.** Downstream tasks supported by representations of street intersections & segments

| Article | Downstream task |
|---|---|
| [27] | street type classification |
| [38] | street type classification and speed limit classification |
| [97] | measuring location trajectory similarity |

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