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## RESEARCH ARTICLE

# Few-Shot Learning-Based Lesser-Known POI Category Estimation Based on Syntactic and Semantic Information

LANDY RAJAONARIVO<sup>ID</sup> AND TSUNENORI MINE<sup>ID</sup>, (Member, IEEE)

Department of Advanced Information Technology, Faculty of Information Science and Electrical Engineering, Kyushu University, Fukuoka 819-0395, Japan

Corresponding author: Landy Rajaonarivo (h.l.rajaonarivo.a03@m.kyushu-u.ac.jp)

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**ABSTRACT** The estimation of points of interest (POI) categories is essential in several contexts, such as land use estimation, POI and itinerary recommendation in the tourism sector, and so on. Most of these approaches are based on well-known POIs and use information such as people's mobility or check-in data. This information is not or rarely available for lesser-known POIs. However, these lesser-known POIs cannot be ignored because of this lack of information, as they may be important to local people in terms of their culture and history and worth discovering by tourists or local authorities. To address this challenge, we propose an approach based on the techniques of coupling the syntactic and semantic analysis of data via a knowledge graph using Few-shot learning (FSL) and Light Graph Convolution Network (LightGCN). The FSL technique allows us to work with very little data, which not only works with lesser-known POIs but also reduces the complexity in terms of tasks and execution time. The results show that our approach outperforms the baseline approaches and that considering the semantic aspect of the data via Linked Open Data (LOD) significantly improves the results of the approach based on the syntactic analysis alone.

**INDEX TERMS** POI category estimation, few shot learning, LightGCN, syntactic and semantic analysis, knowledge graph, linked open data, social media data.

## I. INTRODUCTION

A point of interest (POI) can be defined as a place or a tourist event that tourists can visit or discover during their visit. They can be places of nature, history, religion, sport, etc., or places to discover the culture of the local people, or places where tourists can access services such as food, accommodation, recreation, transport, etc. Some POIs are very well-known and often recommended by tourist offices, others are not. If we search for a known POI, we can get at least 500,000 results via Google and this can rise to over 100 or 200 million. They are also present on well-known travel and tourism sites such as TripAdvisor, Foursquare, Yelp, etc., and have a large number of comments and photos (at least 100 comments or 200 photos). For the purposes of this work, a POI is considered lesser-known if the Google

results are less than 500,000 and the POI is not present or is present but with a very low number of comments and photos (for example, less than 20) on the well-known travel and tourism sites mentioned above. Table 10 shows some examples of lesser-known POI. In some cases, lesser-known POIs are important to local people because they allow them to learn, remember, and share their culture, and to communicate and share moments with each other at cultural and historical events. These POIs may be disadvantaged by standard tourist office approaches or POI recommendations due to a lack of information or ignorance. The aim of this work is to add value to this type of POIs by collecting information about them, estimating their categories if they are not available, and considering them in data recommendation systems. However, since they are lesser known, what data and approaches could be used to achieve these goals? We propose an approach based on several techniques, each of which has its own contribution to make to achieve the objectives, and the

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combination of which gives promising results. As in recent years people are used to sharing their travels or visits on social networks, information from these sources can provide relevant information, and even if only a few people visit lesser-known POIs and share this information, this small amount of information can be exploited thanks to Few-shot learning (FSL). We have adopted the use of information from Twitter.

The main contributions of this paper are as follows: 1) We define the concept of lesser-known POIs and addressed the importance of estimating their categories. 2) We propose a novel FSL-based lesser-known POI category estimation method that uses LightGCN [1] with the coupling of the syntactical and semantic information via the knowledge graphs and the Linked Open Data (LOD). 3) We conducted extensive experiments on POI datasets consisting of different categories and areas in Japan. The experimental results show the superiority of our FSL-based model.

## II. RELATED WORK

The POI estimation approaches are often used to solve other research problems such as: recommending POI, estimating the next POI, estimating the categories of spaces used in given geographical areas, etc. The information used is geographical information such as land use, POI location, and neighborhood characteristics, temporal information such as POI opening days or hours, check-in, meteorological information, information on people's mobility, information from social networks such as comments, shared photos, etc. We can classify the used techniques into four groups: those that use rule-based systems, semantics, Natural Language Processing (NLP), and the coupling of NLP and semantics.

Reference [2] proposes an approach for estimating POI categories using data on land use, mobility, and people's check-ins. Their aim is to classify land use according to people's mobility and activity patterns. They also use data from social networks such as *Sina Weibo* and have proposed rules for estimating POI categories based on the available spatio-temporal and mobility data. Reference [3] also uses check-in data to determine the category of the next POI. They use the attention mechanism and assign different weights to historical records, then employ probability techniques. In [4], more than 150 rules were defined by experts in order to match keywords in POI names and syntactic patterns to POI categories. Reference [5] uses NLP techniques to estimate the categories of POIs based on their names, land use information, and the distribution of POIs in the study area.

Some approaches have introduced the notion of semantics for POI category estimation. The semantic refers to the relationships between temporal information and POIs [6], spatial information and POIs [7], [8], [9], [10], or spatio-temporal information and POIs [11]. Some of these approaches consider the hierarchical relationships between categories [6]. Some approaches use a knowledge graph to represent the relationships between data [12], [13].

Approaches using NLP and the semantic analysis of data have been proposed in order to make recommendations [14], [15], [16], [17]. To do this, they extract user preferences and POI features from comments and sentiments collected via social networks using NLP techniques. They also use time, space, and weather data. Semantics is more concerned with the similarity (synonym, antonym, etc.) of words using Wordnet or geographical proximity, or the weights of words in categories that were done manually. Some approaches use semantic analysis such as capturing dependencies between check-ins [17]. We have not found any approaches that use the knowledge graph generated by dependency parsing coupled with semantics to estimate POI categories. Reference [18] proposes an approach to extract semantic links from places by combining it with content analysis of travel blogs using NLP and generating a graph of POIs. The semantic information concerns only geographical information. The syntactic dependency of words has also been studied. The words generated by NLP can be used to describe POIs. The aim of this approach is not to estimate POI categories, but to see the importance of information in travel blogs. It uses rich information such as the descriptive text of the blogs and dependency analysis, but these dependency links are lost and are not present in the knowledge graph.

The approaches presented in this section differ according to the data and techniques used. In terms of the data used, much of it is not available for lesser-known POIs, such as geographic information (latitude or longitude) or land use, because many of the lesser-known POIs do not have information on Google Map or Open Street Map, information about people's mobility, check-ins, or opening hours. In terms of techniques, rule-based systems are complicated to set up and require experts to define the rules. They are often dedicated to specific data, specific locations or countries, and specific languages. The syntactic analysis used in this field of category estimation is very basic, based only on tokenization and word repetition. The analysis of syntactic dependencies between words is often ignored, although this could provide relevant information. The semantic analysis focuses mainly on geography, more specifically on the geographical proximity between POI. Some approaches use external sources such as Wordnet to add semantic information. The use of Linked Open Data (LOD) and semantic concepts from LOD is not mentioned in these approaches. All of them work on a large amount of data and on known POI.

## III. PROPOSED APPROACH

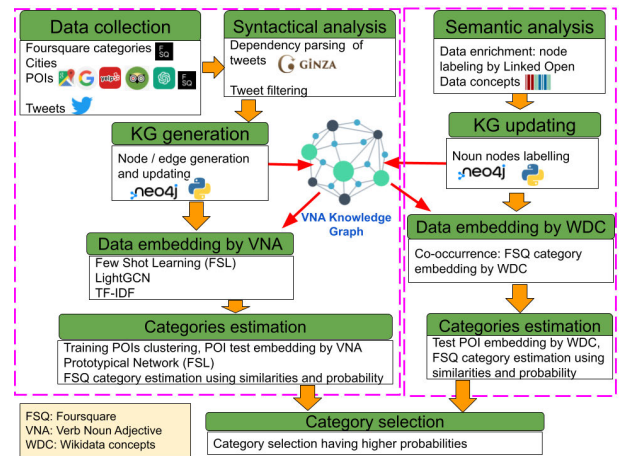
We propose an approach based on the Few-shot learning (FSL) and Light Graph Convolution Network (LightGCN) techniques and the coupling of syntactic and semantic analyses via knowledge graphs. The FSL technique allows us to work with very little data and to generalize. This corresponds to our problem, allowing us not only to work with lesser-known POIs that have very little information to exploit but also to significantly reduce the complexity of the

tasks and the processing time. LightGCN allows POIs with similar characteristics to be brought closer together and POIs with different characteristics to be separated by embedding. This can be useful for data clustering. The syntactic and semantic analysis of the data aims at embedding the POIs via the verbs, nouns, and adjectives (VNA) extracted by syntactic analysis and via semantic concepts by matching the extracted data with the Linked Open Data (LOD). These two analyses complement each other. The use of knowledge graphs allows us to exploit not only the extracted data but also the syntactic and semantic links between them.

Why is it important to link the syntactic information with the semantic information? We may encounter ambiguous data for both large and small data cases. Let us take two examples of POI: P1 and P2. Suppose P1 has different sentences associated with it, such as: play with penguins, ride a horse, feed the chickens. The variety of verbs and nouns does not help the systems estimate the category of POI P1 based on the syntactic information. However, the introduction of the semantic aspect makes it possible to identify the concepts related to the nouns, such as “animal”, “taxon”, etc., and these concepts are characteristic concepts of the category “zoo”, which allows us to estimate that P1 could be of the zoo type. The semantic aspect is only complementary to the syntactic aspect since the nouns enriched here are extracted from the syntactic links with the POI. Let’s assume that P2 is described by the following sentences: eat chicken, grill chicken, drink juice, eat a delicious meal. In this context, it is rather the syntactic analysis that helps to estimate the category of P2, since the verbs (eat, grill, drink), nouns (juice), and adjectives (delicious) are properties characteristic of restaurants. The chicken is ambiguous because it is characteristic of both zoos and restaurants. The coupling of syntactic and semantic aspects removes this ambiguity by linking chicken to the concept of “food and drink” because the juice is also related to this concept and the verbs are related to restaurants. The semantic aspect can then be used to estimate categories when the syntactic aspect fails or to confirm or resolve the results of the syntactic aspect when there are ambiguities. Our approach takes POIs and tweets about each POI as input (tweets containing the name of the given POIs) and outputs a list of estimated categories for each input POI.

**A. PROBLEM DEFINITION**

In this section, we explain the Few-shot learning (FSL) approach on which our approach is based. FSL is defined as a machine learning model that is able to generalize from a few training examples [19]. This approach is usually formed by N-way-K-shot classification and meta-learning. Suppose we have  $C$  categories of POIs. To form a task, we randomly select  $N$  categories of  $C$  and  $K$  POIs from the POIs that have labels in the  $N$  selected categories. Suppose we have a set of training tasks  $\mathcal{T}_{train}$  and testing tasks  $\mathcal{T}_{test}$ , where  $\mathcal{T}_{train} = \{T_1, T_2, \dots, T_m\}$  and  $\mathcal{T}_{test} = \{T_{m+1}, \dots, T_{m+t}\}$ . Each task consists of a data set for training called the “support



**FIGURE 1. POI category estimation approach using syntactic and semantic information.**

set” and a data set for testing called the “query set”. The training task set is used to train and define the learning parameters, whereas the test task set is used to evaluate the performance of the system that has used the learning parameters. Let us denote the data set used in task  $T_i$  as  $D_i = \{D_i^{supp}, D_i^{query}\}$  and the categories as  $C_{T_i}$ . Therefore, the data set of the  $\mathcal{T}_{train}$  will be  $D_{train} = \{D_1, D_2, \dots, D_m\}$  and the data test in  $\mathcal{T}_{test}$  will be  $D_{test} = \{D_{m+1}, \dots, D_{m+t}\}$  where  $|D_1^{supp}| = |D_2^{supp}| = \dots = |D_{m+t}^{supp}| = K$ . Note that there are no common elements between the categories:

$$\bigcap_{T_i \in \mathcal{T}} C_{T_i} = \emptyset$$

Usually,  $K$  is a small number (e.g. 1, 5, 10). Each dataset  $D$  consists of a set of POI, which we can define as follows  $D = \{(x_j, y_j)\}$  where  $x_j$  is the  $j^{th}$  POI in  $D_j$  and  $y_j$  is the set of labels of  $x_j$ .

The meta-learning problem then consists in approximating the function  $f$  with parameters  $\theta$  as follows for each task  $T_i$ :

$$y \approx f(D_i^{supp}, x, \theta) \quad \text{where } (x, y) \in D_i^{query} \quad (1)$$

The result value of  $\theta$  should minimise the sum of the loss function  $\mathcal{L}$  on each task, which is defined as follows:

$$\theta^* = \arg \min_{\theta} \sum_{D_i \in D_{train}} \sum_{(x,y) \in D_i^{query}} \mathcal{L}(f(D_i, x, \theta), y) \quad (2)$$

**B. POI CATEGORY ESTIMATION USING THE COUPLING OF SYNTACTIC AND SEMANTIC INFORMATION**

Fig. 1 shows the process for estimating POI categories. This process is divided into two main modules: estimation via syntactic information on the left and estimation via semantic information on the right.

**1) POI CATEGORY ESTIMATION VIA SYNTACTICAL INFORMATION**

The syntactical module is composed of five steps:

(i) **Data collection:** The data collection consists of collecting 4 types of data: (a) selecting the Foursquare

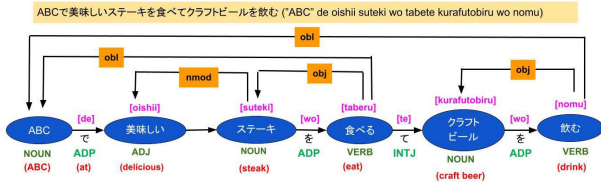


FIGURE 2. Dependency parsing.

categories to consider, (b) selecting the cities of the study areas, (c) selecting well-known and lesser-known POI by using different platforms to check their popularity, and (d) collecting related tweets for each collected POI by using the Twitter API.<sup>1</sup>

(ii) **Syntactical analysis:** The syntactical analysis extracts dependency information in tweets. Fig. 2 shows an example of dependency parsing. As more than 90% of tweets collected are written in Japanese, we use Japanese universal dependency rules<sup>2</sup> and the Ginza<sup>3</sup> API for dependency parsing. We can see in Fig. 2 that each word is represented by a node and it can be of different types as noun, verb, adjective, etc. The nodes are connected by syntactic links such as *obj*, *obl*, *nmod*, etc. Referring to this sentence (“I eat delicious steak and drink craft beer at ABC”). Even if we do not know the categories of the ABC, we can guess that it is a place for eating and drinking on the basis of the verbs, nouns, and adjectives that characterize it. We believe that verbs, nouns, and adjectives (VNA) allow us to describe the characteristics of POIs. Tweets that do not contain at least two of these elements and that are syntactically linked to each other will be ignored at this stage.

(iii) **Knowledge graph generation/updating:** The knowledge graph (KG) generation consists of automatically generating and updating graphs based on the syntactical relationships detected during the previous steps. These graphs are formed by nodes and edges, where the nodes represent the word (verbs, nouns, and/or adjectives), while the edges represent two group types of relationships between words, such as syntactic relationships (e.g. *nmod*, *obj*, etc.) and proximity relationships between two words (words that follow each other in a sentence). Let  $G = (\mathcal{N}, \mathcal{E})$  denote a syntactic KG,  $\mathcal{N}$  a set of nodes, and  $\mathcal{E}$  a set of edges that make up the graph. Let  $\mathcal{N}_{vb}$ ,  $\mathcal{N}_{nm}$ ,  $\mathcal{N}_{adj}$  be the respective sets of verb, noun and adjective type nodes, where  $\mathcal{N} = \mathcal{N}_{vb} \cup \mathcal{N}_{nm} \cup \mathcal{N}_{adj}$ .  $\mathcal{N}$  is defined as follows:  $\mathcal{N} = \{v = (v_{name}, v_{type}, v_{occ}, v_{tweet\_ids})\}$  where  $v_{name}$ ,  $v_{type}$ ,  $v_{occ}$  and  $v_{tweet\_ids}$  are respectively the name of the node, its type, its frequency of occurrence and the list of tweets containing it.  $\mathcal{E} = \{e = (e_{type}, v_i, v_j, w_{ij}, pr_{ij}), v_i, v_j \in \mathcal{N}, w_{ij} \in \mathbb{N}\}$  where  $e_{type}$  is the type of relation,  $w_{ij}$  is the number of times  $v_i$  and  $v_j$  are syntactically linked,  $pr_{ij}$  is the list of particles linking  $v_i$

<sup>1</sup><https://developer.twitter.com/en/use-cases/do-research/academic-research>

<sup>2</sup><https://universaldependencies.org/u/dep/>

<sup>3</sup><https://megagonlabs.github.io/ginza/>

and  $v_j$  according to the tweet collection,  $\mathbb{N}$  is a set of natural numbers.

(iv) **Data embedding via VNA:** Data embedding consists of embedding POIs via verbs, nouns, and adjectives (VNA) by querying the KG and extracting VNA having relationships with the considered POI. The selection of VNAs involves the TF-IDF technique [20], the aim of which is to be able to prioritize the most specific VNAs for each POI. Note that the TF-IDF technique is applied here to VNAs generated from syntactic KGs and not from tokenization as in standard TF-IDF applications. Let us denote  $F_x = \{(v, \sigma_v^x), v \in \mathcal{N}, \sigma_v^x \in \mathbb{R}\}$  as the set of features that allow us to describe the POI  $x$ , where  $\sigma_v^x$  is the weight of the node  $v$  related to the POI  $x$ ,  $\mathbb{R}$  is a set of real numbers.  $F_x$  is given by the following equation:

$$F_x^i = \Phi(G_i, x, p) \quad (3)$$

where  $\Phi$  is a function that queries the knowledge graph  $G_i$  and collects VNA nodes that have syntactic relations with the node  $x$  within a path distance less than  $p$  from  $x$ . The value of  $\sigma_v^x$  is equal to the sum of the weight  $w_{ij}$  of each edge  $e_{ij}$  that formed the path from the node  $x$  to the node  $v$ .

To generate the descriptive VNA embedding vectors, we need to determine the vector attribute. We assume that the POIs in the same task of FSL should have the same vector attribute and they are generated from the POIs in the “support set”. The vector attribute is defined as the common features of a set of POIs. The vector attribute of a task  $\mathcal{T}_i$  denoted  $F_{\mathcal{T}_i}$  is defined as follows:

$$F_{\mathcal{T}_i} = \bigcup_{x \in D_i^{supp}} \Phi(G_{\mathcal{T}_i}, x, p) \quad (4)$$

Assuming that  $d$  is the desired vector attribute size, the duplicate elements in  $F_{\mathcal{T}_i}$  are removed by aggregating their weight values  $\sigma$  to the unique element, and then the elements are ordered according to  $\sigma$ , the vector attribute is defined as follows  $F_{\mathcal{T}_i}^* = \{\psi_a\}$  where  $\psi_a \in F_{\mathcal{T}_i}$ ,  $a \in [1..d]$ ,  $\forall a < b, \sigma_{\psi_a} > \sigma_{\psi_b}$ . The descriptive VNA vector of a POI  $x$  according to the vector attribute  $F_{\mathcal{T}_i}^*$  is defined as follows:  $x = (u_1, u_2, \dots, u_d)$  where

$$u_a = \begin{cases} \sigma_{\psi_a}^x & \psi_a \in F_x^{\mathcal{T}_i} \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

The values of  $u_a$  are normalized where

$$\sum_{a=1}^d u_a = U$$

We propose to use LightGCN to bring POIs belonging to the same category closer together and to move POIs belonging to different categories away from each other. Each POI in a given task  $\mathcal{T}_i$  is embedded by LightGCN [1].

Clustering is applied to the embedding vectors generated by LightGCN, where DBSCAN [21] is used as the clustering method and the cosine measure for calculating the similarity in clustering. The cosine measure is used for clustering. Two similarity measures are proposed to estimate the labels of

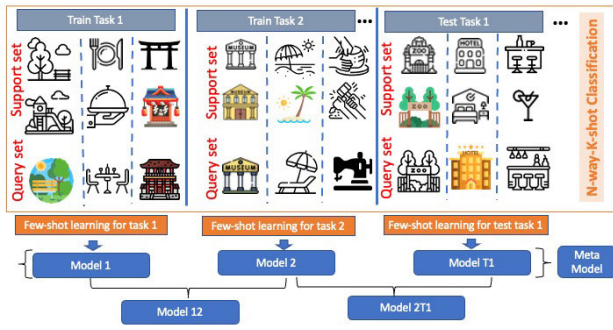


FIGURE 3. Few shot learning for multi-label estimation.

a given POI: the similarity measure related to the original embedding noted  $sim_{prop}$  and the cosine similarity related to the LightGCN embedding. The similarity between two POIs  $x_1$  and  $x_2$  is defined as follows:

$$sim(x_1, x_2) = \alpha \cdot sim_{prop}(x_1^O, x_2^O) + \beta \cdot cosine(x_1^{LG}, x_2^{LG}) \quad (6)$$

where  $\alpha + \beta = 1$ ,  $x^O$  the original VNA embedding vector, and  $x^{LG}$  the LightGCN embedding vector ( $\alpha$  is 1 and  $\beta$  is 0 if LightGCN is ignored).

(v) **POI category estimation:** This module uses the FSL to estimate the POI categories. Fig. 3 illustrates our proposal of FSL for multi-label estimation. We have adopted the use of *prototypical networks* [22] as a type of meta-learning that belongs to the family of approaches using the prior of similarity. This stage consists of first selecting the more appropriate model according to Fig. 3, then applying the prototypical network to the task corresponding to the selected model. Suppose we want to estimate the labels of a POI  $x$ , the approach of the model selection based on the features  $F_x$  and the common features or vector attribute  $F_{\mathcal{T}_i^*}$  of each task  $\mathcal{T}_i$  is as follows:

$$g(x) = m, \gamma_m = \max \gamma_z, \quad \forall z \in [1..|\mathcal{M}|] \quad (7)$$

$\gamma$  is defined by two parameters:  $\gamma^{inter}$  and  $\gamma^{weight}$  where  $\gamma_z^{inter} = |F_x \cap F_{\mathcal{T}_i^*}|$ ,  $\gamma_z^{weight} = \sum \sigma_{\psi_a}^x \forall \psi_a \in F_x \cap F_{\mathcal{T}_i^*}$ . When we define the more appropriate model, the estimation of the labels of a POI  $x$  is defined as follows:

- embed POI  $x$  according to the VNAs that have syntactical links with it in the KG, then embed this generated embedding vector by using LightGCN.

- obtain the closest clusters by comparing the distance value between  $x$  and the representatives of the clusters using cosine and LightGCN embedding vectors. The cluster representative vector is the average of the values of the POIs that make it up. This generates a learning parameter that is the size of the nearest clusters to be considered that we have noted  $z$ .

- recover all POIs in the closest clusters and compute the similarity between  $x$  and each POI in the closest clusters using the similarity measure defined in the equation (6). This will generate the optimal value of the learning parameter  $\alpha$ .

TABLE 1. POI embedding with verbs.

POI	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$	...	$v_V$
$P_1$	$\sigma_{v_1}^1$	$\sigma_{v_2}^1$	-	-	$\sigma_{v_5}^1$	$\sigma_{v_6}^1$	...	$\sigma_{v_V}^1$
$P_2$	-	$\sigma_{v_2}^2$	$\sigma_{v_3}^2$	-	-	$\sigma_{v_6}^2$	...	$\sigma_{v_V}^2$
...								
$P_p$	$\sigma_{v_1}^p$	$\sigma_{v_2}^p$	$\sigma_{v_3}^p$	$\sigma_{v_4}^p$	$\sigma_{v_5}^p$	$\sigma_{v_6}^p$	...	$\sigma_{v_V}^p$

$v_i$ : verb ( $v_i \in \mathcal{N}_{vb}$ ),  $\sigma_{v_i}^x$ : weight of the verb  $v_i$  for the POI  $p_x$

TABLE 2. POI embedding with nouns.

POI	$n_1$	$n_2$	$n_3$	$n_4$	$n_5$	$n_6$	...	$n_N$
$P_1$	$\sigma_{n_1}^1$	$\sigma_{n_2}^1$	-	-	$\sigma_{n_5}^1$	$\sigma_{n_6}^1$	...	$\sigma_{n_N}^1$
$P_2$	-	$\sigma_{n_2}^2$	$\sigma_{n_3}^2$	-	-	$\sigma_{n_6}^2$	...	$\sigma_{n_N}^2$
...								
$P_p$	$\sigma_{n_1}^p$	-	$\sigma_{n_3}^p$	$\sigma_{n_4}^p$	-	$\sigma_{n_6}^p$	...	$\sigma_{n_N}^p$

$n_i$ : noun ( $n_i \in \mathcal{N}_{nm}$ ),  $\sigma_{n_i}^x$ : weight of the noun  $n_i$  for the POI  $p_x$

TABLE 3. POI embedding with adjectives.

POI	$a_1$	$a_2$	$a_3$	$a_4$	$a_5$	$a_6$	...	$a_A$
$P_1$	$\sigma_{a_1}^1$	-	$\sigma_{a_3}^1$	-	$\sigma_{a_5}^1$	$\sigma_{a_6}^1$	...	$\sigma_{a_A}^1$
$P_2$	$\sigma_{a_1}^2$	$\sigma_{a_2}^2$	$\sigma_{a_3}^2$	-	-	$\sigma_{a_6}^2$	...	$\sigma_{a_A}^2$
...								
$P_p$	$\sigma_{a_1}^p$	-	$\sigma_{a_3}^p$	$\sigma_{a_4}^p$	-	$\sigma_{a_6}^p$	...	$\sigma_{a_A}^p$

$s_i$ : adjective ( $a_i \in \mathcal{N}_{adj}$ ),  $\sigma_{a_i}^x$ : weight of the adjective  $a_i$  for the POI  $p_x$

- retrieve all labels appearing in the nearest clusters and assign a value  $\omega$  to each label based on the similarity of the POIs in the nearest clusters and the POI  $x$ . Suppose  $x_1$  and  $x_2$  in the nearest clusters are both labelled by the category  $c^i$ ,  $\omega_x^i = sim(x_1, x) + sim(x_2, x)$ .

- calculate the probability that a category  $c_i$  can be a label of the POI  $x$ , which is defined as follows: Suppose  $d_x^i = 1 - \omega_x^i$ .

$$p(y = c_i | x) = \frac{exp(-d_x^i)}{\sum_{j=1}^L exp(-d_x^j)} \quad (8)$$

Table 1, 2 and 3 present respectively the structure of the POI embedded vectors via verbs, nouns and adjectives. The number of items in the embedded vector is limited by  $d$ , so  $V, N, A \leq d$ .

## 2) POI CATEGORY ESTIMATION VIA SEMANTIC INFORMATION

The semantic module is composed of four steps:

(i) **Semantic analysis:** The semantic analysis detects the nodes as types of nouns that can be enriched with Linked Open Data (LOD), more precisely with Wikidata.<sup>4</sup> At this stage, for each POI, we query the KG and retrieve the associated nouns, then call the Wikidata API<sup>5</sup> to check if the nouns are available in Wikidata. If a noun is available, it can be an instance (e.g., park ABC) or a concept (e.g., park). We retrieve the information about the instance or concept and its concept parents by considering the following attributes: “instance-of” and “subclass-of”.

(ii) **KG updating:** The KG updating aims to enrich the KG by labeling the nodes according to the

<sup>4</sup><https://www.wikidata.org/>

<sup>5</sup>[https://www.wikidata.org/wiki/Wikidata:REST\\_API](https://www.wikidata.org/wiki/Wikidata:REST_API)

information about semantic concepts from Wikidata (e.g., park, animal, mountain, food, etc.). At this stage, a node  $v$  presents in Wikidata has complementary attributes as follows:  $v = (vwdId, vwdName, vwdConcepts)$ , where  $vwdId, vwdName, vwdConcepts$  are the information collected from Wikidata (Wikidata identity, name and related concepts).

(iii) **Data embedding by Wikidata concepts:** This module consists of embedding POIs via WikiData Concepts (WDC). To do this, we first define the WDC corresponding to each Foursquare category by collecting all POIs belonging to each category, querying the KG to retrieve the nouns related to all POIs, and retrieving all WDC related to these nouns. We use a weighting system to define the importance of the WDC corresponding to each category based on co-occurrence. We combine all the WDCs corresponding to each category and select the most common WDCs (top  $W$ ). At the end of this stage, we automatically generated a type of dictionary that matches the Foursquare categories to the WDCs (e.g., the Foursquare category “park” is linked with the wikidata concepts “garden, flower, recreation, etc.”). For each Foursquare category  $c$ , the list of WDCs of  $c$  (noted  $\Gamma_c$ ) is defined as follows:  $\forall c \in C, \Gamma_c = \{(wcd_i, \eta_{wcd_i}^c), i \in [1..W]\}$  where  $wcd_i$  is a Wikidata concept, and  $\eta_{wcd_i}^c$  is the weight of the  $wcd_i$  for the category  $c$ ,  $W$  is the maximum size of the list.

(iv) **POI category estimation:** This stage consists of estimating the more similar Foursquare category according to the WDC that describes a POI. To do so, we retrieve the WDC related to the given POI  $x$  (noted  $\tilde{F}_x^i$ ) by querying the KG  $G_i$ .  $\tilde{F}_x^i$  is given by the following equation:

$$\Gamma_x^i = \Theta(G_i, x, p) \quad (9)$$

where  $\Theta$  is a function that queries the knowledge graph  $G_i$  and collects the Wikidata concept of the noun nodes that have syntactic relations with the node  $x$  within a path distance less than  $p$  from  $x$ . The value of  $\sigma_v^x$  is equal to the sum of the weight  $w_{ij}$  of each edge  $e_{ij}$  that formed the path from the node  $x$  to the node  $v$ .

We then apply a probability measure to define the more similar Foursquare categories according to the POI  $x$ .

$$p(y = c_z|x) = \frac{\sum_{wcd_i \in (\Gamma_{c_z} \cap \Gamma_x)} \eta_{wcd_i}^{c_z}}{\sum_{c \in C} \sum_{wcd_j \in (\Gamma_c \cap \Gamma_x)} \eta_{wcd_j}^c}, \quad (10)$$

where  $\Gamma_{c_z}$  and  $\Gamma_x$  are respectively the WDC related to a given category  $c_z$  and the POI  $x$ .

Table 4 present the structure of embedded vector of POIs via semantic concepts.

Algorithm 1 presents the global process of the POI category estimation based on syntactic and semantic information.

### C. TIME AND SPACE COMPLEXITY OF THE PROPOSED APPROACH

We have three types of data: the tweets collected for each POI, the POI that is used for training in FSL, and the POI

TABLE 4. POI embedding with semantic concepts.

POI	$c_1$	$c_2$	$c_3$	$c_4$	$c_5$	$c_6$	..	$c_C$
$P_1$	$\sigma_{c_1}^1$	$\sigma_{c_2}^1$	-	-	$\sigma_{c_5}^1$	$\sigma_{c_6}^1$	..	$\sigma_{c_n}^1$
$P_2$	-	$\sigma_{c_2}^2$	$\sigma_{c_3}^2$	-	$\sigma_{c_5}^2$	$\sigma_{c_6}^2$	..	$\sigma_{c_n}^2$
..								
$P_p$	$\sigma_{c_1}^p$	-	$\sigma_{c_3}^p$	$\sigma_{c_4}^p$	-	$\sigma_{c_6}^p$	..	$\sigma_{c_n}^p$

$c_i$ : concept,  $\sigma_{c_i}^x$ : weight of the concept  $c_i$  for the POI  $p_x$

### Algorithm 1 POI Category Estimation

$F_{x,v}^g \leftarrow \text{getVerbAttribute}(x, g)$   $\triangleright$  via Eq. 3  
 $F_{x,n}^g \leftarrow \text{getNounAttribute}(x, g)$   $\triangleright$  via Eq. 3  
 $F_{x,a}^g \leftarrow \text{getAdjectiveAttribute}(x, g)$   $\triangleright$  via Eq. 3  
 $\Gamma_x^g \leftarrow \text{getWDCAttribute}(x, g)$   $\triangleright$  via Eq. 9

**Require:**  $|F_{x,v}^g|$  or  $|F_{x,n}^g|$  or  $|F_{x,a}^g|$  or  $|\Gamma_x^g| > 0$

$\triangleright \mathcal{M}$ : set of models,  $\mathcal{T}$ : set of tasks

$\mathcal{M}_m \leftarrow \text{getRelatedModel}(F_x^g, \mathcal{M}, \mathcal{T})$   $\triangleright$  via Eq. 7

$F_{x,v}^m \leftarrow \text{embedPOIByModel}(F_{x,v}^g, \mathcal{M}_m)$   $\triangleright$  via Eq. 5

$F_{x,n}^m \leftarrow \text{embedPOIByModel}(F_{x,n}^g, \mathcal{M}_m)$   $\triangleright$  via Eq. 5

$F_{x,a}^m \leftarrow \text{embedPOIByModel}(F_{x,a}^g, \mathcal{M}_m)$   $\triangleright$  via Eq. 5

$\xi_{x,v} \leftarrow \text{estimateCategory}(F_{x,v}^m, \mathcal{M}_m)$   $\triangleright$  via Eq. 8

$\xi_{x,n} \leftarrow \text{estimateCategory}(F_{x,n}^m, \mathcal{M}_m)$   $\triangleright$  via Eq. 8

$\xi_{x,a} \leftarrow \text{estimateCategory}(F_{x,a}^m, \mathcal{M}_m)$   $\triangleright$  via Eq. 8

$\xi_{x,WDC} \leftarrow \text{estimateCategory}(\Gamma_x^g, \mathcal{M}_m)$   $\triangleright$  via Eq. 10

$\triangleright \xi_{x,-} = \{(c, p_c)\}$  a set of estimated categories with their probability

$\xi_x \leftarrow \xi_{x,v} \cup \xi_{x,n} \cup \xi_{x,a} \cup \xi_{x,WDC}$

$\xi_x^+ \leftarrow \{\}$

**for each**  $c \in \xi_x$  **do**

$v_c \leftarrow \rho \cdot p_c + \tau \cdot \lambda_c$   $\triangleright$  where  $\rho + \tau = 1$ ,  $\lambda_c$  the

appearance rate of  $c$  in  $\xi_x$   $\triangleright$  The closer  $\lambda_c$  is to 1,

the more it was estimated as a category for any embedding: verb, noun, adjective, semantic concept embedding

$\xi_x^+ \leftarrow \xi_x^+ \cup \{(c, v_c)\}$

**end for**

$\xi_x^* \leftarrow \{c^*\}$   $\triangleright c^*$  is a category in  $\xi_x^+$  having the maximum value of  $v$

**for each**  $c \in \xi_x^+$  **do**

**if**  $v_{c^*} - v_c \leq \epsilon$  **then**

$\xi_x^* \leftarrow \xi_x^* \cup \{c\}$

**end if**

**end for**

**Return**  $\xi_x^*$

that is used as a test. The size of each data is respectively  $TW, N \cdot K$  and  $P$ . In order to define the complexity of our approach, we need to define the complexity of the FSL and the complexity of the category estimation processing.

FSL involves four processes, the complexity of each of which is as follows:

- Data processing:  $O(c_1 \cdot N \cdot K \cdot TW)$
- Data embedding:  $O(c_2 \cdot N \cdot K \cdot TW)$
- Clustering:  $O(N \cdot K \cdot \log(N \cdot K))$
- Model generation:  $O(c_3)$

TABLE 5. Test data distribution.

City/categories	Park	Museum	Shrine	Zoo	Craft store
Hokkaido	5	4	4	4	3
Kyoto	2	2	5	2	4
Tokyo	4	4	4	3	2
Kagawa	3	3	4	2	1
Fukui	2	2	3	1	3
Shimane	3	3	3	4	2
Okinawa	3	4	3	2	4
Total	22	22	26	18	19
	107				

The complexity of the FSL is then  $O(c \cdot N \cdot K \cdot TW + N \cdot K \cdot \log(N \cdot K))$ , where all constant  $c_1$ ,  $c_2$  and  $c_3$  are considered as  $c$ .

The category estimation involves five processes, the complexity of each of which is as follows:

- Data processing:  $O(c_1 \cdot P \cdot TW)$
- Data embedding:  $O(c_2 \cdot P \cdot TW)$
- Appropriate model selection:  $O(c_4)$
- Data embedding via model:  $O(c_5)$
- Category estimation:  $O(c_6)$

The complexity of the category estimation is then  $O(c \cdot P \cdot TW)$ , where all constant  $c_1$ ,  $c_2$ ,  $c_4$ ,  $c_5$  and  $c_6$  are considered as  $c$ .

The complexity of our approach is then equal to the sum of  $O(c \cdot N \cdot K \cdot TW + N \cdot K \cdot \log(N \cdot K))$  and  $O(c \cdot P \cdot TW)$ . Since  $N$ ,  $K$  and  $P$  are much less than  $TW$ , the complexity of our approach is  $O(TW)$ .

## IV. EXPERIMENT AND ABLATION STUDY

### A. DATASET

In this section, we describe the values of the different elements we defined in the “Data Collection” module in Fig. 1. We have selected seven root categories (“arts and entertainment”, “landmarks and outdoors”, “community and government”, “travel and transportation”, “retail”, “dining and drinking”) from ten in Foursquare and nine categories (park, craft store, metro station, museum, shopping mall, shrine, zoo, bar, hotel) within these root categories that we consider relevant to our research. To ensure a diversity of cities, we selected eight prefectures in Japan such as Fukuoka, Hokkaido, Kyoto, Tokyo, Kagawa, Fukui, Shimane, and Okinawa. Fukuoka is our study area. Hokkaido is Japan’s northernmost prefecture and its climate is between temperate and polar, with milder summers and harsher winters. The city of Kyoto is known for the presence of at least 17 major historical monuments recognized by Unesco, such as temples, shrines, and castles. Tokyo is located in the center of the country. The city of Tokyo is one of the world’s largest cities and the largest of Japan’s 47 prefectures. It is the main tourist destination in Japan. Kagawa Prefecture is best known for its size (it is the smallest prefecture in Japan) and its gastronomy. Fukui and Shimane are both small prefectures. They are located on the coast of the Sea of Japan. Okinawa Prefecture is the southernmost prefecture in Japan. It has a subtropical oceanic climate and a warm climate

throughout the year. Okinawan culture is quite different from other parts of Japan. These prefectures were chosen to see if our model was able to estimate the categories of POIs in small and large cities, as well as those of less known, moderately known, and very known POIs located in areas with different climatic conditions. To select POIs for training, we used POIs from the city of Fukuoka, and to obtain labeled POIs, we selected POIs available on Foursquare and used the Foursquare API. POIs from other prefectures are all used to evaluate our approach. The POIs used for the evaluation were selected manually using different platforms such as Google, Google map, Yelp (Yp), TripAdvisor(TA), Foursquare (FSQ), Jalan(JL), ChatGPT. These are used to check the popularity of POIs. For each prefecture, we tried to select an average of 4 POIs, including 1 very well-known POI, 1 moderately well-known POI, and 2 lesser-known POIs. As lesser-known POIs are rarely available in very well-known APIs, we had to make the selection manually. Parameters have been defined to classify the POIs. For Google, four parameters are used: the number of search results (GR), the presence of the POI in Maps (M), and the number of photos (P) and reviews (R). For the other platforms, we use the three parameters M, P, and R. Table 5 shows the POIs distribution of data used in the test. For small prefectures such as Kagawa, Fukui, and Shimane, most of the POIs are lesser-known. Once the POIs are selected, we use the Twitter API<sup>6</sup> to collect the tweets related to those POIs. Table 6 shows the data distribution used in training. For each POI, we have collected the related tweets for 3 years (2020, 2021, and 2022). As the number of results for each query is limited to 500, we split the queries into one query per 3 months, so we have 12 queries for 3 years. If a POI is well-known, we can collect 500 tweets per query, so 6000 tweets for 3 years and 18000 tweets for 3 POIs in the training database (support sets). We can see from Table 6 that the numbers of tweets for lesser-known POIs in the support and request sets are low compared to the number of tweets for well-known POIs.

### B. BASELINE APPROACHES

In our previous work, we used BERT as a baseline. Since classical approaches use text documents or contextual texts for label estimation, they are not suitable for very short texts such as tweets. The estimation rate is very low due to inappropriate embedding techniques. In this current study, we focus on the use of our embedding techniques and the impact of using or not using each technique. We compare our model to three approaches that use our data embedding but do not use FSL. In these baseline approaches, instead of dividing data and processes into tasks, all data is used as a whole for training. Table 7 illustrates the results of these baseline approaches (rows: 1, 2, and 3).

### C. ABBREVIATION AND ACRONYM

Table 8 shows the list of abbreviations and acronyms.

<sup>6</sup><https://developer.twitter.com/en/docs/twitter-api>

TABLE 6. Train data distribution.

Set/#tweets	T1			T2			T3		
	Park	Museum	Shopping-mall	bar	shrine	Zoo	education	train station	Craft store
Support (3 POIs)	6821	10624	3166	407	2277	3969	1943	546	329
Query (2 POIs)	6116	2393	774	159	2338	115	90	130	280

TABLE 7. Ablation of the study.

	Approaches/F1			Park		Museum		Shrine		Zoo		Craft store		Average	
	FSL	LGCN	TF-IDF	A	F1	A	F1	A	F1	A	F1	A	F1	A	F1
1	N	Y	Y	0.41	0.10	0.53	0.36	0.42	0.27	0.41	0.46	0.64	0.37	0.48	0.31
2	N	N	Y	0.73	0.43	0.79	0.52	0.80	0.58	0.70	0.49	0.82	0.64	0.77	0.53
3	N	N	N	0.63	0.13	0.73	0.42	0.80	0.57	0.63	0.42	0.80	0.58	0.72	0.42
4	Y	N	Y	0.67	0.36	0.81	0.53	0.81	0.61	0.78	0.59	0.83	0.64	0.78	0.55
5	Y	N	N	0.66	0.24	0.82	0.61	0.85	0.70	0.74	0.55	0.85	0.64	0.78	0.55
6	Y	Y	N	0.74	0.29	0.77	0.44	0.88	0.71	0.77	0.47	0.79	0.43	0.79	0.47
7	Y	Y	Y	<b>0.89</b>	<b>0.74</b>	<b>0.90</b>	<b>0.80</b>	<b>0.90</b>	<b>0.72</b>	<b>0.93</b>	<b>0.84</b>	<b>0.89</b>	<b>0.75</b>	<b>0.90</b>	<b>0.77</b>

FSL:Few-shot learning LGCN:LightGCN A:Accuracy F1:F-score

TABLE 8. List of abbreviations and acronyms.

Abbreviation	Definition
POI	Point of interest
FSL	Few-shot learning
LightGCN	Light Graph Convolution Network
LOD	Linked Open Data
NLP	Natural Language Processing
VNA	Verb, Noun, Adjective
KG	Knowledge Graph
DBSCAN	Density-based spatial clustering of applications with noise
WDC	Wikidata Concept
Yp	Yelp
TA	TripAdvisor
FSQ	Foursquare
JL	Jalan
GR	Google Results
TF-IDF	Term Frequency-Inverse Document Frequency

#### D. MODEL SETUPS

To set up the model, the following elements need to be defined, such as the distribution of tasks, categories, and POIs for the Few-shot learning (FSL) and the organization of the knowledge graphs. For the FSL, we applied the 3-way-3-shot classification by random selection and generated three tasks:  $\mathcal{T}_1$ ,  $\mathcal{T}_2$ ,  $\mathcal{T}_3$ . The categories of POIs treated in  $\mathcal{T}_1$  are park, museum, and shopping center, those treated in  $\mathcal{T}_2$  are bar, shrine, and zoo and those treated in  $\mathcal{T}_3$  are a hotel, train station, and craft store. For each task and category, three POIs are used as support, and two POIs are used as queries. So we use 45 POIs for FSL.  $\mathcal{T}_1$ ,  $\mathcal{T}_2$  are used as training tasks and  $\mathcal{T}_3$  is used as a test task. After applying meta-learning, we obtain the values of our learning parameters such as the similarity threshold for clustering, the value of  $\alpha$  in Eq. 6, the size of the vector embedding, etc. We have generated six models:  $\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3, \mathcal{M}_{12}, \mathcal{M}_{13}, \mathcal{M}_{32}$ . The knowledge graphs are generated for each city, so we have eight knowledge graphs. The generation of models proceeds as follows: models  $\mathcal{M}_1, \mathcal{M}_2, \mathcal{M}_3$  respectively used the data in tasks  $\mathcal{T}_1, \mathcal{T}_2$  and  $\mathcal{T}_3$  for training and test whereas the models  $\mathcal{M}_{12}, \mathcal{M}_{13}, \mathcal{M}_{32}$  used respectively for training and test, the combination of the data in tasks  $\mathcal{T}_1$  and  $\mathcal{T}_2, \mathcal{T}_1$  and  $\mathcal{T}_3, \mathcal{T}_3$  and  $\mathcal{T}_2$ . Each model contains the optimal values of the learning parameters according to the

data used in training. For a given POI whose categories are to be estimated and a selected model  $\mathcal{M}$  for estimation, the characteristic of the POI is compared to those of the POIs in the training of the model  $\mathcal{M}$ .

The vector attribute of the model  $\mathcal{M}_{ij}$  denoted  $F_{\mathcal{T}_{ij}}$  is defined as follows:

$$F_{\mathcal{T}_{ij}} = F_{\mathcal{T}_i} \cup F_{\mathcal{T}_j} \quad (11)$$

Assuming that  $d$  is the desired vector attribute size, the duplicate elements in  $F_{\mathcal{T}_{ij}}$  are removed by aggregating their weight values  $\sigma$  to the unique element, and then the elements are ordered according to  $\sigma$ , the vector attribute is defined as follows  $F_{\mathcal{T}_{ij}}^* = \{\psi_a\}$  where  $\psi_a \in F_{\mathcal{T}_{ij}}, a \in [1..d], \forall a < b, \sigma_{\psi_a} > \sigma_{\psi_b}$ .

Let  $F_x^g$  be the vector attribute of the POI  $x$  in the knowledge graph  $G_g$  that contains it. Its value is defined in Eq. 3. The vector attribute of the POI  $x$  related to the model  $\mathcal{M}_{ij}$  (noted  $F_x^{ij}$ ) is defined as follows:

$$F_x^{ij} = (u_1, u_2, \dots, u_d) \text{ where}$$

$$u_a = \begin{cases} \sigma_{\psi_a}^{x,g} & \text{if } \psi_a \in F_x^g \\ 0 & \text{otherwise.} \end{cases} \quad (12)$$

$\sigma_{\psi_a}^{x,g}$  is the weight of the attribute  $\psi_a$  for the POI  $x$  in the knowledge graph  $G_g$ .

The values of  $u_a$  are normalized where

$$\sum_{a=1}^d u_a = U$$

#### E. EXPERIMENTAL RESULTS

Table 9 presents the results of our approach based on the syntactic analysis (top, noted  $\mathcal{R}_{Syn}$ ) and the coupling of the syntactic and semantic analysis of the data (bottom, noted  $\mathcal{R}_{SS}$ ). Looking at the global average values, we can see that the global averages for accuracy and F1 in  $\mathcal{R}_{SS}$  are considerably higher than those in  $\mathcal{R}_{Syn}$ . If we focus on the averages for all the columns corresponding to the POI



**TABLE 9.** Evaluation of the multi-label estimation approach with and without semantic module (SM) (Top: wo. SM, Bottom: w. SM).

	City/FI	Park		Museum		Shrine		Zoo		Craft store	
		Approach with syntactic analysis ( $\mathcal{R}_{Syn}$ )									
		A	F1	A	F1	A	F1	A	F1	A	F1
1	Hokkaido	0.77	0.33	0.79	0.41	0.83	0.5	0.75	0.34	0.83	0.67
2	Kyoto	0.75	0.33	0.83	0.75	0.7	0.4	0.92	0.83	0.83	0.5
3	Tokyo	0.92	0.75	0.71	0.17	0.96	0.96	1	1	1	1
4	Kagawa	0.83	0.67	0.89	0.67	0.83	0.5	1	1	0.67	0
5	Fukui	0.83	0.5	1	1	0.89	0.667	1	1	0.72	0.22
6	Shimane	0.78	0.5	0.67	0.2	0.89	0.67	0.83	0.59	0.66	0.33
7	Okinawa	0.78	0.5	0.75	0.25	0.83	0.56	0.75	0.65	0.92	0.75
8	Average wo. SM	0.81	0.51	0.81	0.49	0.85	0.61	0.89	0.77	0.80	0.5
9	Standard deviation wo. SM ( $\sigma$ )	0.06	0.16	0.11	0.32	0.08	0.18	0.11	0.26	0.13	0.34
10	Global average wo. SM	<b>avg(A)=A=0.83, <math>\sigma(A)=0.17</math>, avg(F1)=0.59, <math>\sigma(F1)=0.27</math></b>									
		Approach with the coupling of syntactical and semantic information ( $\mathcal{R}_{SS}$ )									
11	Hokkaido	<b>0.93</b>	<b>0.87</b>	<b>0.87</b>	<b>0.79</b>	0.83	0.5	<b>0.83</b>	<b>0.58</b>	<b>0.89</b>	<b>0.83</b>
12	Kyoto	<b>0.83</b>	<b>0.5</b>	0.83	0.75	<b>0.87</b>	<b>0.6</b>	0.92	0.83	<b>0.92</b>	<b>0.83</b>
13	Tokyo	0.92	<b>0.87</b>	<b>0.87</b>	<b>0.67</b>	0.96	0.96	1	1	1	1
14	Kagawa	0.83	0.67	<b>1</b>	<b>1</b>	<b>0.92</b>	<b>0.75</b>	1	1	<b>1</b>	<b>1</b>
15	Fukui	<b>0.92</b>	<b>0.83</b>	1	1	<b>1</b>	<b>1</b>	1	1	<b>0.78</b>	<b>0.33</b>
16	Shimane	<b>0.83</b>	<b>0.56</b>	<b>0.83</b>	<b>0.67</b>	0.89	0.67	<b>0.92</b>	<b>0.83</b>	<b>0.75</b>	<b>0.5</b>
17	Okinawa	<b>0.94</b>	<b>0.89</b>	<b>0.92</b>	<b>0.75</b>	0.83	0.56	<b>0.83</b>	<b>0.67</b>	0.92	0.75
18	Average w. SM	0.89	0.74	0.90	0.80	0.90	0.72	0.93	0.84	0.89	0.75
19	Standard deviation w. SM ( $\sigma$ )	0.05	0.16	0.07	0.14	0.06	0.19	0.07	0.17	0.10	0.25
20	Global average & $\sigma$ w. SM	<b>avg(A)=0.90, <math>\sigma(A)=0.07</math>, avg(F1)=0.77, <math>\sigma(F1)=0.18</math></b>									

A:Accuracy F1:F-score avg: average  $\sigma$ : standard deviation

categories, we can see that the averages for accuracy (A) and F-score (F1) in  $\mathcal{R}_{SS}$  are all higher than those in  $\mathcal{R}_{Syn}$  (rows 9 and 18). The cells from rows 1 to 10 are  $\mathcal{R}_{Syn}$  values whereas those from rows 11 to 20 are  $\mathcal{R}_{SS}$  values. If we look closely at the cell values in  $\mathcal{R}_{SS}$ , we can see that 60% of the results have been improved (values in bold) thanks to the coupling of the syntactic and semantic information. Note that 63% of the unchanged cells have accuracy values greater than 0.9 and F1 values greater than 0.75, which can already be considered optimal, hence no change. This enables us to say that the coupling of syntactic and semantic information brings significant improvements compared to the approach based on syntactic analysis alone. For all the prefectures, the accuracy values vary between 0.75 and 1, and for F1 between 0.33 and 1 (Table 9, rows 11 to 17). Compared to the others, the “zoo” category is well estimated, with 70% of the prefectures having accuracy values greater than 0.9. The majority of zoos are of the zoological park type, so they belong to two categories: park and zoo. If the accuracy and F1 values are equal to 1, this means that the system detects exactly the two true categories. Fukui is a small prefecture and most of the POIs there are little known, but 80% of the categories have accuracy values greater than 0.9, and 60% have accuracy values equal to 1 (row 15). Similarly, for Tokyo, the best-known and largest prefecture in Japan, 50% of the categories have accuracy values greater than 0.9, and 80% have accuracy values equal to 1 (row 13). This enables us to say that our approach allows us to estimate the categories of the lesser-known POIs as well as the well-known ones. In addition, even if POIs have different characteristics depending on their geographical location, our

system manages to estimate their categories to a large extent. For example, the characteristics of zoos in the far north and the far south are completely different because the animals and the climate are not the same. Animals in the north are more likely to be able to withstand extreme cold, while those in the south are more likely to be able to withstand high temperatures. What’s more, geographical location can have an impact on people’s culture.

#### F. ABLATION AND LIMITATION OF THIS STUDY

Table 7 presents the results of the comparison of our approach with the baseline approaches that do not use FSL (rows: 1, 2, 3), and also with other approaches based on our proposal, but which may or may not include certain modules (rows 4, 5 and 6). Only row 7 includes the semantic module. We can see that for all the columns, row 7, which presents the results of our proposal (FSL, LightGCN, coupling of syntactic and semantic information, and TF-IDF), contains the optimal values. The vast majority of results from the approaches without FSL are poor. We can see in rows 2 and 3 that the use of TF-IDF improves the results slightly for all categories. Rows 4 and 5 do not include either LightGCN or semantic analysis, but the accuracy values for the categories: museum, shrine, and craft store are greater than 0.8. This means that our method of embedding with VNA, generated with the syntactic analysis on which our approach is based, is very important and can give significant results even without LightGCN and semantics. The other modules are used to improve performance.

The limitation of our approach is the layout of the data. Some lesser-known POIs have no information at all

**TABLE 10. Examples of lesser-known POIs please refer to Section IV-A for details on abbreviations.**

POI/Sources	Google		Yp	FSQ	TA	Jl	ChatGPT	Our approach			
	GR	M,P,R	M,P,R	M,P,R	M,P,R	M,P,R	C,D,E	# TW	Estimated categories	A	F1
Ryūsen hamono (龍泉刀物), Fukui	219K	(Y,14,12)	(Y,0,0)	(Y,0,0)	N	(Y,9,0)	(Cutlery or Blades, N, N)	349	Retail, Travel and transportation	1	1
Kametani yōgyō (亀谷窯業), Shimane	8K	(Y,16,10)	(Y,0,0)	N	N	(Y,7,1)	N	41	Retail Dining and drinking	1	1
Noguchi senpo (野口染舗), Hokkaido	16K	(Y,10,7)	N	N	N	(Y,15,2)	N	63	Retail Travel and transportation	1	1

Yp: Yelp, FSQ: Foursquare, TA: TripAdvisor, JL: Jalan  
 GR: Google search result, M: Google maps, P: Photos, R: Reviews, C (Categories), D (Details), E (Explanation)  
 Y (Yes), N (No), #TW (number of tweets), A (Accuracy), F1 (F-score)

on Twitter. Our approach is therefore unable to estimate the categories of these POIs when there is no text to analyze. On the other hand, the advantage of our approach is that it is generic and can be used with any text, not just tweets, and with some adaptation can be used with text in other languages.

**G. EXAMPLE OF LESSER-KNOWN POIS**

Table 10 shows some examples of lesser-known POIs. “Ryuusen hamono” is a handicraft factory and shop where we can buy or sharpen the knives we normally use, or listen to a lecture by a craftsman. “Kametani Yougyou” is a boutique for the sale and manufacture of handmade ceramics using traditional techniques. It also offers apprentice workshops. “Noguchi Senpo” is an artisan factory that works on fabrics, especially on operations related to kimono, dyeing, processing, manufacturing, and cleaning. They also propose some workshops such as the coloring of fabrics. Their numbers of tweets are very low for a period of 3 years (2020, 2021, 2022). We asked ChatGPT<sup>7</sup> the categories of the POIs in Table 10 by asking the following question: “What is the category of the place called [POI Japanese name]? or Talk about [POI Japanese name]?”. Normally, when we ask ChatGPT, it gives not only the answer related to our question but also some details or explanations. This is the case when we ask this question for well-known POIs. In the case of the first POI (Ryuusen hamono) in Table 10, ChatGPT relies only on the name of the POI to determine its type, there is no detail or explanation, and the detected category which is “cutlery” is not the correct category. ChatGPT is not able to guess the categories of the last two POIs. There is no response at all for these POIs. We can conclude that ChatGPT does not have enough information for these POIs to be able to estimate their categories. The accuracy and F1 values of our approach are very good with precision and F1 equal to 1. We also query our system to get some details about what we can do at these places such as: “Ryusen cutlery teaches you how to make cutlery” (88 tweets), “Making a bell at Kametani Pottery” (55 tweets). The examples shown in Table 10 are POIs that may be of interest to tourists and that may be specific to the cities in

**TABLE 11. POI category estimation using ChatGPT.**

	City/F1	Park	Museum	Shrine	Zoo	Craft store
1	Hokkaido	***: 40% *: 20% ⊖: 40%	*: 75% ⊖: 25%	*: 100%	*: 100%	*: 100%
2	Kyoto	***: 50% **: 50%	*: 100%	***: 40% *: 60%	*: 100%	*: 50% ⊖: 50%
3	Tokyo	***: 50% **: 50%	*: 100%	***: 25% *: 75%	*: 100%	⊖: 100%
4	Kagawa	*: 100%	*: 100	***: 25% *: 75%	*: 100%	*: 100%
5	Fukui	*: 100%	*: 100	*: 100%	*: 100%	*: 100%
6	Shimane	*: 100%	*: 100%	*: 100%	*: 100%	*: 50% ⊖: 50%
7	Okinawa	*: 100%	*: 100%	*: 100%	***: 50% *: 50%	*: 100%

\*\*\*: More than two information about the specific POI, \*\*: one or two information,  
 \*: POI is not in database, the estimation based only on the name of the POI  
 ⊖: POI is not in database and ChatGPT cannot estimate the POI category (no detail at all)  
 Realized on 2023/09/13

which they are located. We can say that our approach makes it possible to promote these types of POIs by including them in recommendation systems and having them discovered by tourists. The fact that ChatGPT cannot provide information about them shows that this information is difficult to find. Our approach, therefore, offers advantages in terms of complexity, where search and page consultation times, as well as information assembly and analysis tasks, are significantly reduced.

Table 11 shows the rates of the POIs in the database whose categories are good, moderate, and not estimated by ChatGPT. We use four rating symbols such as \*\*\*, \*\*, \*, and ⊖. If at least one of the categories of a given POI is detected by ChatGPT and the latter provides more than two pieces of information about the POI (e.g., the specificity of the POI, what we can do there, the places to visit nearby, its history, etc.), we rate this type of result as \*\*\*. If ChatGPT has recognized at least one of the categories of the given POI and provides one or two pieces of information about the POI and the rest is general information about POIs in the same category, we rate this type of result as \*\*. If the POI is not in the ChatGPT database but this latter has recognized one of the categories of the POI based on its name, we rate this kind of result as \*. For this case, ChatGPT provides generic information. We rate the result as symbol ⊖ if the POI is not

<sup>7</sup><https://chat.openai.com/>

in the ChatGPT and this latter cannot be recognized in its categories i.e., it gives no information at all.

We can see from Table 11 that about 50% of the parks in large prefectures such as Hokkaido, Kyoto, and Tokyo are well recognized by ChatGPT (★ ★ ★). However, most of the POIs in other categories such as museums, shrines, zoos, and craft stores are not in the ChatGPT database even if they are located in large prefectures and the estimation of their category based only on the name (★, row 1,2,3). Almost all the POIs in our database in medium and small prefectures are not in the ChatGPT database (rows 4, 5, 6, 7) and the estimation of their category is based only on the name (★). All POIs in our database that have “museum”, “zoo”, and “craft store” as categories are not in the ChatGPT database. The category of some of them is not recognized at all by ChatGPT.

#### H. APPLICATION OF APPROACH ON TOURISM AND URBAN PLANNING

The combination of semantic and syntactic information gives us knowledge graphs that are rich in information and allows us to assess their reliability. These knowledge graphs are essential for recommending POIs or tourist itineraries, but also for answering questions that tourists and tourist offices may ask. Examples of questions that tourists or tourist offices might ask are: What/Where/Why/How to visit, discover local things, eat, go for a drink, buy tickets, sleep? Knowledge graphs can be used to answer these questions by constructing sentences from the verbs, nouns, adjectives, and particles that form the nodes and edges of the graphs. This is made possible by syntactic information that has been established and represented in knowledge graphs. The idea is to regenerate sentences from tweets, taking into account the question asked and the frequency of the information to ensure reliability. On the other hand, syntactic graphs do not guarantee against nonsense errors. For example, the information “I ate some building” is syntactically correct but makes no sense. Hence the interest in coupling this information with the semantic information, because it avoids this kind of problem. Thanks to the semantic information, we have the semantic concepts of the nodes in the graphs, such as food, place, tourist site, animal, means of transport, etc. This information allows us to check the compatibility between nouns, verbs, and adjectives in the generated sentences. The questions asked and the answers given enable local authorities to discover new information that they may not have been aware of before. This can help them to promote the area and recommend places or events to tourists. This approach also makes it possible to update publicly available ontologies such as Wikidata by discovering new instances of concepts such as local food, lesser-known tourist places and events, etc. This is not the only advantage of setting up semantic information. It is essential for the recommendation, taking into account semantically similar or different nodes, in order to encourage tourists to discover things related to their interests or to extend these interests by making them discover things that are a little different from what they prefer.

#### V. CONCLUSION AND FUTURE WORK

We have proposed an approach to estimate POI categories. The specificity of this approach lies in the use of Few-shot learning, LightGCN, and coupling of the syntactic and semantic information via knowledge graphs and LOD. The results show that our approach is able to estimate the categories of lesser-known POIs as well as very well-known POIs. The integration of the semantic aspect significantly improves the results of the proposed approach based on the syntactic analysis. This information is generic in terms of semantic graph and syntactic graph generation and category estimation using machine learning but language-specific in terms of dependency parsing. The results of the category estimation via ChatGPT show that many POIs in large, medium, and small prefectures are not recognized by ChatGPT and it is worth estimating the category of these POIs and recommending them to tourists. In the future, we intend to consider other data sources in order not to penalize POIs that do not have tweets. The data sources we can consider are other social networks, comments on tourism platforms, websites, etc. For our approach, the processing does not require any specific structures but accepts any form of text (long or short). This approach to estimating POI categories will be integrated into a recommendation system based on machine learning to recommend lesser-known POIs to tourists and provide them with detailed information about these POIs. Another line of research that we have already begun to explore is the consideration of information in other languages, such as French and English. The aim of this approach is twofold: to evaluate the generalizability of our approach, which uses texts as input data, and to analyze the differences and similarities between countries in terms of culture, geography, history, and the behavior and preferences of their populations or tourists. The analysis of genericity will allow us to determine which aspects change depending on the language and which aspects remain generic.

#### APPENDIX

##### REQUESTS TO AND RESULTS FROM ChatGPT

This section presents some examples of results provided by ChatGPT for the rates ★ ★ ★, ★, and ⊖ respectively:

- Maruyama Park (円山公園): “円山公園 (*Maruyama Park*) is a **famous park located in Sapporo, Hokkaido, Japan**. It is a public park and is often categorized as a “city park” or “urban park.” Maruyama Park is known for its **beautiful cherry blossoms in the spring**, a large weeping cherry tree, and the **Hokkaido Shrine**, making it a popular destination for both locals and tourists. While it’s primarily a natural and recreational area, **it also has cultural and historical significance due to the presence of the shrine**”.

- Neopark Okinawa (ネオパークオキナワ): “ネオパークオキナワ (*Neopark Okinawa*), also known as **Neo Park Okinawa**, is a **wildlife and botanical park located in Okinawa, Japan**. It falls under the category of a “zoological park” or “wildlife park.” These types of parks are designed to provide visitors with the opportunity to observe and learn

about a variety of animal species, including both native and exotic animals, in settings that mimic their natural habitats. Additionally, Neopark Okinawa may also have botanical gardens and areas dedicated to showcasing various plant species, which adds to its appeal as an educational and recreational destination.”

- Okunoyu Park (の湯公園): “I’m sorry, but **I don’t have specific information about a place named “奥の湯公園” in my database, and it doesn’t appear to be a widely known or famous location. To determine the category of this place, you may need to provide additional context or conduct local research to find out more about its features and purpose. Typically, a place with “公園” (park) in its name in Japan would be a park or a recreational area, but the specific category would depend on its design, amenities, and intended use.**”, consulted on 2023/09/11.

- Amano Konya (天野紺屋) which is a craft store in Shimane prefecture, in Japan: “I’m sorry, but **I don’t have specific information about a place named “天野紺屋” in my knowledge base. It’s possible that this place is not widely recognized or is a local establishment that doesn’t have significant global or national recognition.**”, consulted on 2023/09/11.

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**LANDY RAJAONARIVO** received the master’s degree in intelligent systems and multimedia from Hanoi University, Vietnam, in 2014, the master’s degree in enterprise digital content engineering from the University of La Rochelle, France, and the Ph.D. degree in computer science from ENIB, Brest, France, in 2018. From 2018 to 2020, she was a Research Engineer with the University of Pau, France. Since 2020, she has been a Postdoctoral Researcher with Kyushu University, Fukuoka, Japan. She published papers in relevant journals and conferences in her field, such as Intelligent User Interfaces (IUI), *User Modeling and User-Adapted Interaction (UMUAI)*, *International Journal of Geo-Information (IJGI)*, and *Web Intelligence and Intelligent Agent Technology (WI-IAT)*. Her research interests include recommendation systems, natural language processing, machine learning techniques, and multi-agent systems. Her awards and recognitions include the JSPS Research Fellowship for Young Researchers, in 2021, and the IIAI International Congress on Advanced Applied Informatics Honorable Mention Award, in 2022.



**TSUNENORI MINE** (Member, IEEE) received the B.E. degree in computer science and computer engineering and the M.E. and D.E. degrees in information systems from Kyushu University, in 1987, 1989, and 1993, respectively. He is currently an Associate Professor with the Department of Advanced Information Technology, Faculty of Information Science and Electrical Engineering, Kyushu University. He is also leading several collaboration research projects with various companies and academic institutions to develop technologies and theories that are both practical and academically novel. His research interests include the development of real-world services using artificial intelligence techniques, especially natural language processing, text mining, data mining, recommendation, and multi-agent systems. He received the Best Paper Award from the Journal of the Information Processing Society of Japan (IPJS) for his work on a parallel parsing algorithm, in 1993, and the IPJS Activity Contribution Award, in 2014.