Location Digest: A placeness service to discover community experience using social media

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***Abstract*—Sociality plays a vital role in our daily lives. Be it a hyper-local search for finding a restaurant to eat or a global search for your next travel destination; as humans, we tend to make our choices considering the social atmosphere offered by the place. Placeness, in this context, refers to the social and cultural semantics of the space under consideration and represents the distinctiveness of a place. In this paper, we aim to discover placeness as the exemplary community experience associated with a given location. We do this by, first adopting a flexible methodology for mining placeness, and then proposing a novel unsupervised mechanism for discovering placeness. Furthermore, we implement placeness as an IoT service for Smart City dwellers, calling it as *Location Digest*, by using GS1 standards-based Open Language for the Internet of Things (Oliot) platform. We report a sufficiently high F1-score of 0.81 for our unsupervised placeness discovery mechanism and present Location Digest as an essential service for assisting tourists in a Smart City.**

***Index Terms*—social media, geo-tagged images, smart tourism**

I. Introduction

With the advent of Smart Cities, accessibility of Internet is becoming affordable, fast and ubiquitous. This has paved a way for participatory culture of contributing and consuming community media facilitated by social media platforms such as Flickr, Facebook, Instagram, Foursquare, and YouTube. Amongst the different modalities of community media content (such as image, video, and text), geo-tagged data is of particular interest. A geo-tagged data is the one which contains at least a latitude and longitude as part of its metadata. Consequently, enormous geo-tagged data at/near a given location, contributed by individual members of a community, morphs from individual life-logs into a collective community experience. The knowledge of this community experience (in a given spatial area) characterizes the "understood reality" [1] and represents the "distinctiveness of a place" [2], in contrast to the "spatial opportunity" and has been the subject of designing computer supported cooperative systems for over two decades. A space, in this context, refers to the physical dimension and represents its bricks-and-mortar setup, whereas, *placeness* refers to the social and cultural semantics (e.g., community experience) of the space under consideration.

Conventionally, placeness has been studied by conducting surveys and interviews. However, the constant evolution of placeness makes the associated analysis always in flux. On the other hand, with the proliferation of Social Media platforms, a significant amount of community contributed content becomes readily available, plausibly offering profound insights into the lifestyle of urban dwellers. Consequently, Computer Scientists have curated and harnessed the dataset for various applications, for instance, to characterize an urban area, and to segment socio-geographical boundaries of a city as shown in Fig. 1. Although notably successful in characterizing the understood reality, previous works fall short in discovering the distinctiveness of a place. As an example, in [3], the authors characterize an urban area as either Life, Work, Shopping, Entertainment, or Food. However, for instance, they do not distinguish between the types of *Entertainment* a community participates, e.g., in Las Vegas vs. Seoul, or the kind of *Food* preferred by community members. Moreover, characterizing or segmenting an urban area results into a strict partitioning that undermines typically mixed compositions of modern cities.

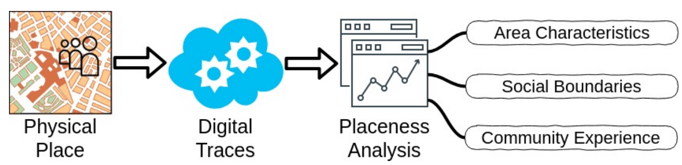

Fig. 1: Process of placeness analysis from social media: Physical places have corresponding digital traces, which are analyzed to discover placeness in various ways.

In this paper, we conduct our placeness exploration based on the fact that an urban area is multifaceted and its dwellers participate in a rich set of activities, leaving digital visual cues on social media platforms. Our goal is then to discover placeness as the various facets experienced by community members of an urban area. To achieve that, at first, we develop a flexible methodology that can comprehensively accommodate heterogeneous data sources and enables to discover knowledge for determining exemplary community experience (placeness) associated with a given location. Then, we investigate the viability of harnessing community contributed geo-tagged images for mining placeness by using state-of-the-art deep neural network (DNN) based algorithms. Furthermore, we implement a placeness service, Location Digest, which we believe can hugely assist tourists in a Smart City. In summary, our contributions are as follows:

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1) We propose a novel unsupervised mechanism for discovering placeness from an unorganized set of images. Our mechanism utilizes DNN features extracted from a pre-trained network with a classical clustering algorithm to discover the mixed compositions of an urban area.
2) We then evaluate the proposed mechanism on a set of geo-tagged community contributed images, collected from around a famous place in South Korea. The F1-score of our approach is reported to be 0.81, with 87.2% precision and 76.4% recall, which is sufficiently high for an unsupervised mechanism.
3) The mined placeness is then implemented as an IoT service, viz. Location Digest, for Smart Cities, by using GS1 standards-based Open Language for the Internet of Things (Oliot) platform [4]. We foresee that such a service can assist tourists in making informed decisions for their travels, for instance, by discovering placeness via Bluetooth beacons on their smartphones or car infotainment systems.

The remainder of this paper is organized as follows: In Section II, we present related works on placeness modeling for public spaces. In Section III, we explain our methodology for discovering placeness as the exemplary community experience. In Section IV, we evaluate the methodology using a dataset curated from Instagram. In Section V, we propose Location Digest, a placeness service for Smart Cities, by utilizing GS1 standards-based Oliot platform. Finally, in Section VI, we conclude the paper and layout possible future works.

II. Related Work

Placeness has been defined diversely in various fields (e.g., Geography, Sociology, and Architecture) and studied from different viewpoints in Computer Science. In this section, we discuss the different perspectives and limitations of the surveyed work.

In [3], the authors characterize an urban area into one of the five categories (Life, Work, Shopping, Entertainment, and Food) by harnessing time information from geo-tagged tweets collected using Twitter. In [5], the authors also make use of time information to classify an urban area as a combination of business, entertainment, and residential by analyzing subway ridership patterns (i.e., number of people boarding and deboarding). In [6], the authors explore ambiance of a place in 13-dimensions (e.g., Loud, Romantic, Trendy, and Conservative) by utilizing images collected from Foursquare. In [7], the authors compute social boundaries of a city, in contrast to municipal demarcations, by using check-in information from Foursquare. In [8], the authors create a network of socially similar urban neighborhoods by analyzing crowd movement patterns using Twitter. Although the surveyed works have been mostly successful in characterizing an urban area, they fall short in discovering the mixed compositions of a place and thus community experience (e.g., Entertainment in Las Vegas vs. Seoul). Another set of research, attempting to solve this issue emerge from computer vision.

Essentially, the task of discovering community experience can be seen as clustering visual variations in an unorganized set of geo-tagged images. In [9], the authors intent to find diverse and representative pictures from an unorganized set of geo-tagged images collected using Flickr, by using a combination of global and local image features. However, their focus is to discover landmarks (e.g., Golden Gate Bridge in San Francisco), instead of community experience. In [10], the authors propose an algorithm for discovering visual variations by clustering images using affinity propagation on SIFT features. However, SIFT features are handcrafted and computationally expensive [11]. Another notable work is from [12], wherein DNN features of a pre-trained network are utilized for unsupervised object classification in a robotic application to sort and store various objects (e.g., hammer, nails, and screwdriver).

In this work, we represent the composition (and therefore community experience) of an urban area as its visual variations on Instagram, which is a popular community media platform and contains a rich set of images [13] capable of facilitating a multifaceted placeness exploration. Furthermore, we present Location Digest as an essential placeness service for supporting tourists in a Smart City.

III. Placeness Discovery Mechanism

In this section, we first describe our research methodology for mining placeness and then proceed to explain each component. To begin with, we can easily observe that physical spaces around us are no longer disjoint from cyber spaces. In fact, there is a whole body of research dedicated to Physical-Cyber-Social computing [14]. Geo-tagged data, in this context, plays a pivotal role for mining placeness and is readily available from social media platforms in various modalities.

However, processing raw data is computationally expensive and in many cases do not generalize as a model because of redundant information. We, therefore, start by performing Feature Extraction for dimensionality reduction, essentially representing our dataset as a collection of feature vectors. Consequently, a data item is considered to be similar with another one, based on Similarity Measurement of feature vectors. After obtaining similarity scores between various data items, the next reasonable step is to Discover Knowledge from the dataset by clustering similar items. Since there can exist multiple clusters, a natural question to ask is "Which data item best represents this cluster?", which turns out to be the Exemplar Community Experience (i.e., placeness).

After mining placeness as the exemplary community experience, we create an IoT service for Smart City dwellers, enabling tourists to discover a place from the perspective of local experts. The overall research methodology is outlined in Fig. 2 and we adopt it for mining placeness using community contributed geo-tagged images.

A. Feature Extraction

To extract features from a given image, we utilize a pre-trained InceptionV3 DNN model [15] on the ImageNet dataset [16] and construct a feature vector of size 2048 from

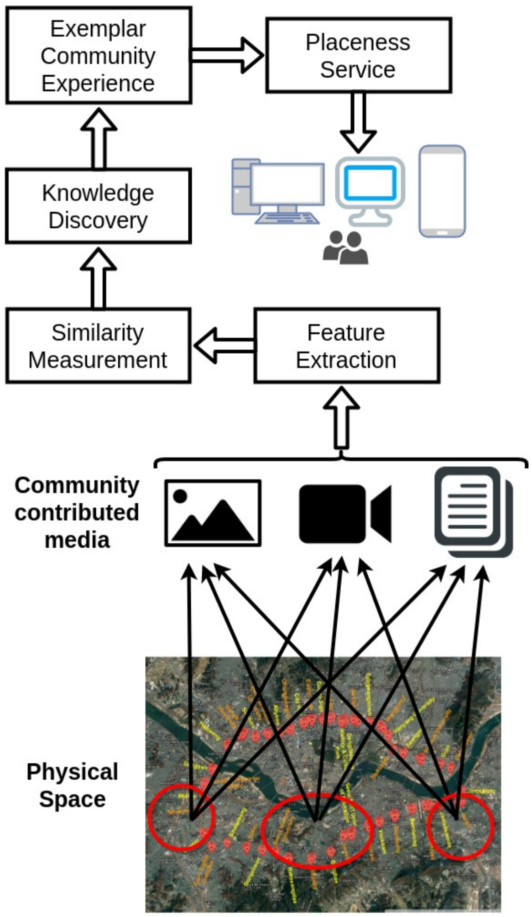

Fig. 2: Research methodology for mining placeness by using community contributed media — Geo-tagged data from physical space represents a virtual place on social media platforms. We utilize this data to discover community experience associated with a space and create a placeness service for smart city dwellers.

the penultimate layer of the model as shown in Fig. 3. These extracted features have recently shown promising results in unsupervised object classification tasks [12], and we believe are a good fit in-general as well for discriminating visual variations present in an unorganized set of images. Although there is no well-known proof explaining the semantic meaning of our feature vector, intuitively, it represents global features of an image. The reason for this intuition comes from the last layer of InceptionV3, which has been shown to accurately predict the 1000 ImageNet categories with less than 5% error. Therefore, in a sense, the second-to-last layer of DNN model captures enough discriminative information.

B. Similarity Measurement

To compute the pairwise distance between our feature vectors, we utilize their cosine similarity. In the domain of text mining, cosine similarity has previously shown promising results [17] to measure the similarity of two documents by using their term-frequency (TF) as feature vectors. TF vectors

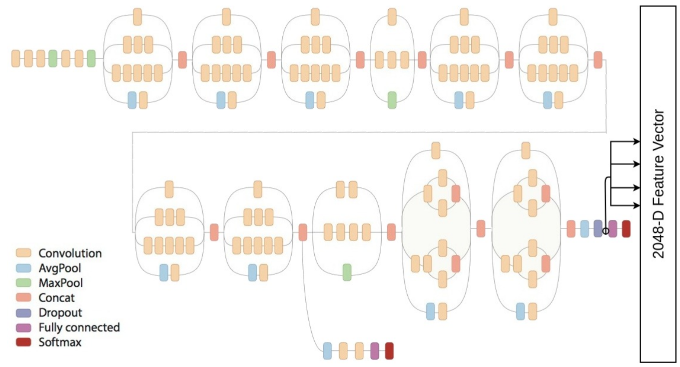

Fig. 3: Feature Extraction from the penultimate layer of a pre-trained InceptionV3 DNN model, resulting a 2048-D vector.

are high dimensional and sparse, similar to the one obtained in our case. We, therefore, choose cosine similarity as our metric for Similarity Measurement. The cosine similarity of two feature vectors, $\mathbf{A}$ and $\mathbf{B}$, is calculated from the dot product and the magnitude of vectors and is therefore affected only by their shared terms:

$$\text{similarity} = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}, \text{ where n = 2048}$$

C. Knowledge Discovery

After fixing our feature space and similarity metric, the next step is to group similar images. We, therefore, cluster the feature vectors using our similarity metric. To avoid deciding the number of visual variations (i.e., the number of clusters) present in the set of images beforehand, we choose to utilize a Hierarchical clustering algorithm. Hierarchical clustering is robust in various aspects; it avoids deciding the number of clusters before performing the actual clustering, enables to choose a custom linkage criteria (and therefore can often find complex cluster shapes), and a dendrogram (resulting out of hierarchical linkages) helps to visualize different clustering granularities.

There are two main classes of Hierarchical clustering; Divisive (top-down), and Agglomerative (bottom-up). A divisive approach starts with all the samples in one big cluster and recursively splits it up. On the other hand, an Agglomerative approach begins with each sample in its own cluster, merging them until all the samples are in one big cluster. In our case, we decided to utilize Agglomerative clustering to evade specifying top-down splitting decisions and instead chose to define bottom-up linkage criteria. Moreover, agglomerative clustering is beneficial in big-data scenarios, since it iterates over a smaller coarse-grained subset of the data.

Consequently, for the bottom-up linkage of clusters, we utilized the ward-criteria [18], which implements Ward's variance minimization algorithm. The algorithm merges two such clusters, that leads to the minimum increase in total within-cluster variance (and hence within-cluster visual variations) after the merge operation. At the end of this step, we obtain a dendrogram, similar to the one shown in Fig. 4, but without highlighted clusters and labels. In the dendrogram tree, each leaf node represents an image from our dataset and begins as the only member of its cluster. As the hierarchical agglomerative algorithm progresses, a cluster links-up with another cluster according to the ward-criteria, until only a single one remains.

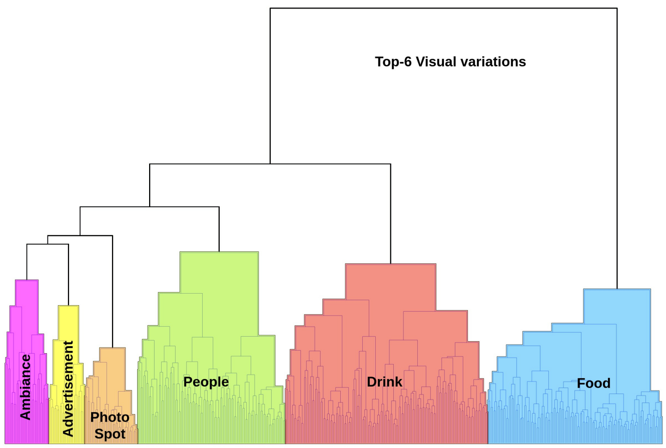

Fig. 4: Dendrogram as a result of Hierarchical Agglomerative clustering. The results are pruned at a depth of 10 for brevity. Top-6 visual variations are highlighted with respective labels.

D. *Exemplar Community Experience*

To compute exemplary community experience, at first, we select top-6 dense clusters from the dendrogram obtained in Fig. 4. We choose top-6 clusters so that one exemplary image from each such visual variation can fit in a typical screen-size of a smartphone or infotainment system. And then, to find an exemplary image from each cluster, we select the one with highest community engagement (i.e., the total number of likes and comments on Instagram). For deciding the label of a visual variation, we manually inspect 80% of randomly sampled images from each cluster and assign the dominant class as its label. Although in our study, we have manually examined 80% of each cluster to decide its label, we shall observe in the next section that the number of images requiring a manual inspection to ascertain the labels can be reduced significantly since the clusters are well-formed.

IV. Experiment and Results

To evaluate our methodology, we curated a dataset of images posted on Instagram geo-tagged around Hongik University station [19], a subway station in Seoul (South Korea), most notably serving the popular surrounding area of Hongik University Street (Hongdae). We chose Instagram as our source of data because its a popular visual-oriented community media platform, hosting images capable of representing diverse visual variations [13] of an urban lifestyle. A total of 278 instagram location-IDs within 200m radius of the station were considered for creating the dataset. To further enrich the visual variations in our dataset, we randomly downloaded 10 images for each time-bin in a day — Night (12AM - 6AM), Morning (6AM - 12PM), Afternoon (12PM - 6PM), and Evening (6PM - 12AM) — by using Instagram APIs [20] from December 1, 2017 to December 31, 2017. All 1240 of the downloaded images are available as public content. A random subset of the dataset is shown in Fig. 5.

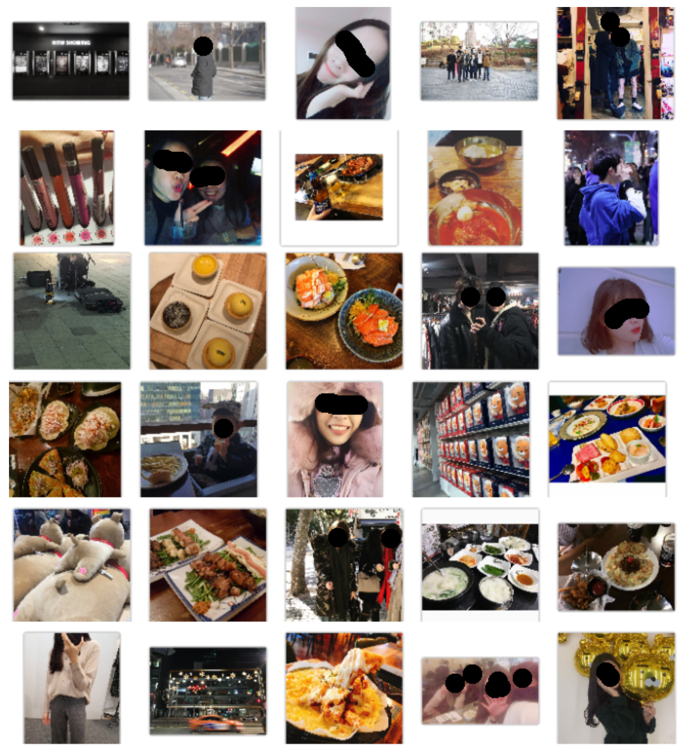

Fig. 5: A random subset of images collected from around Hongik University subway station, notably known for serving the surrounding Hongdae area. Notice that the set offers a mix of unorganized visual semantics (e.g., Food, People, and Ambiance).

We then applied the proposed placeness discovery methodology to our dataset. A manual inspection of top-6 clusters yielded the visually variant labels as (a) Food, (b) Drink, (c) People, (d) Ambiance, (e) Photo Spot, and (f) Advertisement. We show the qualitative results in Fig. 6; each row represents respective labels, with the first column illustrating an exemplar community experience. The corresponding dendrogram is shown in Fig. 4.

On a closer look at the qualitative results, we observe that our unsupervised methodology can discover visual variations in the dataset successfully. In fact, quite surprisingly, it has identified Photo Spot as a famous Kakao-friends toy shop in Hongdae and is also able to offer useful insights about the area, for instance, Ambiance, Food, and Drink. Additionally, People category can be utilized for computing demographics of the urban area and presented to the tourist as a summary to protect the privacy of individual community members.

The dendrogram also draws another interesting observation; notice that if we instead choose top-3 clusters, People category will merge with Ambiance, Advertisement, and Photo Spot, reflecting the fact that people like to take their images and upload on social media with beautiful backgrounds or famous landmarks.

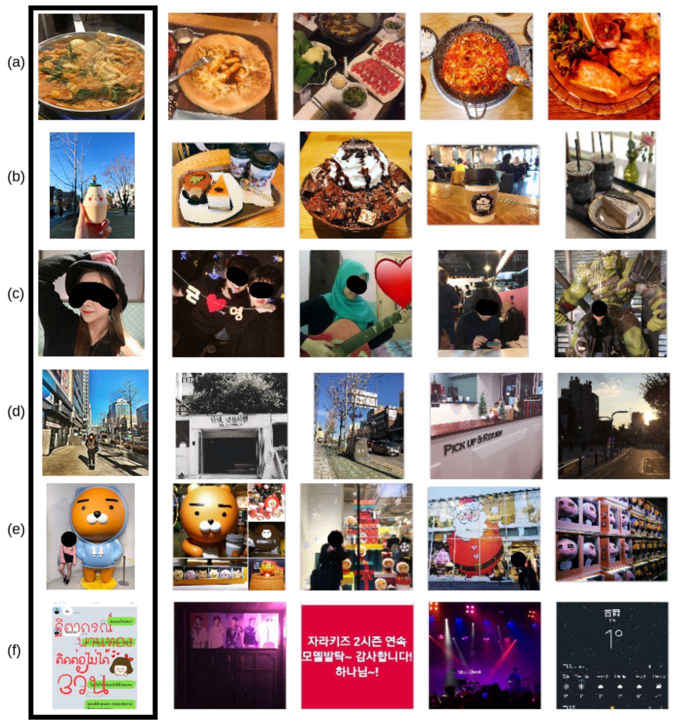

Fig. 6: Top-6 visual variations in the dataset, computed using the unsupervised mechanism discussed in Section III. Notice that in comparison to Fig. 5, the results offer far more organized visual semantics. For instance, visual variation (a) represents Food, (b) Drink, (c) People, (d) Ambiance, (e) Photo Spot (a famous Kakao-friends toy shop in Hongdae), and (f) Advertisement. First column in each row is the exemplary image of respective visual variations and rest of the images are sampled randomly from its cluster.

To quantify the *goodness* of our methodology, we used transfer learning to train a Residential network based classifier [21] with five classes (Food, Drink, People, Ambiance, Photo Spot, and Advertisement) and measured the performance in terms of precision and recall. Precision signifies that "if a class is predicted by our model, how likely is that to be right" and recall signifies that "out of the classes which should have been predicted correctly, how many did our model actually find". Since precision and recall are in fight with each other, we measure F1-score as their harmonic mean:

$$F_1 = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Table I summarizes the precision and recall of each visual variation obtained by applying our methodology. We report an overall F1-score of 0.81, implying that the proposed placeness discovery methodology, although unsupervised, is *sufficiently* precise and robust.

TABLE I: Results: Accuracy matrix

The values show total samples, precision and recall for each visual variation with a probability threshold of 50%. The overall precision and recall is reported to be 87.2% and 76.4% respectively, yielding a F1-score of 0.81.

Variation	Samples	Precision	Recall
Food	195	89.8%	93.5%
Drink	293	88.9%	67.9%
People	436	92.0%	77.6%
Ambiance	215	77.8%	67.7%
Photo Spot	56	81.0%	90.7%
Advertisement	45	83.3%	65.8%

In the next section, we will utilize our methodology to design and implement *Location Digest*, an IoT enabled placeness service for Smart City dwellers.

V. Location Digest: Smart City IoT Service

Crowdsourced social media communication channels (e.g., blogs, forums, and media sites) are a well-known source of information for tourists visiting a foreign country [22]. Nevertheless, all states are known to have their tourism department, usually run by the Government, responsible for providing an easy access of information once a tourist arrives in the country (e.g., at the airport). A few nations provide this service using Information and Communication Technologies (ICTs), for instance, through mobile applications, e.g., South Korea Tourism [23], in addition to relying on conventional ways of distributing printed maps in several languages. Although useful, empirically, the information is handcrafted and deficit in local community experience. To solve this issue, and to provide an easy access mechanism for tourists in a Smart City, we propose Location Digest, a placeness service for the Internet of Things (IoT), based on novel ideas borrowed from supply chain management standards.

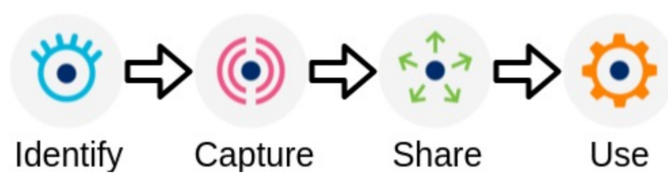

Fig. 7: Four step process in adopting GS1 standards to build interoperable IoT systems

IoT is suffering from platform fragmentation. While various major companies are progressing towards standardization individually or by establishing different consortiums, there is no unified way for normalization. GS1 standards [24] solves the issue of IoT platform fragmentation with its robust identification (ID) system [25] and a four step process to Identify, Capture, Share, and Use the information as shown in Fig. 7.

GS1 ID keys are a globally unique set of ID keys adopted by various industry verticals (e.g., Retail, Healthcare, and

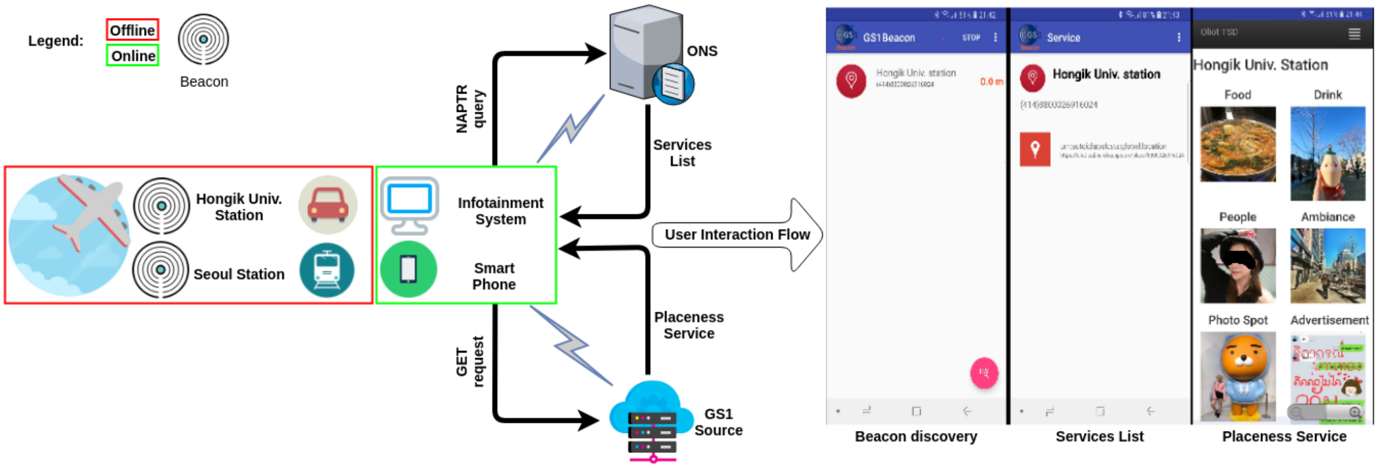

Fig. 8: Placeness Service based on GS1 IoT platform. Global Location Number (GLN) broadcasted by GS1Beacon is utilized for connecting offline physical locations with online services. A NAPTR query is sent to Object Name Service (ONS), which returns a list of services associated with the provided GLN. GS1 Source provides placeness service to user devices, such as an Infotainment System or Smart Phone. A sample user interaction flow using an Android device is shown on the right side.

Transportation & Logistics) and are utilized to identify a comprehensive body of items (e.g., products, locations, and assets). We, therefore, chose to design and implement Location Digest using our previous work on Oliot [4], a GS1 standards-based open-source IoT platform. At first, we describe an example user interaction flow using an Android smart-phone and then explain the platform components used for building the placeness service.

A. *User Interaction Flow*

We foresee an application of Location Digest in Smart Cities for Tourism, especially in high density and well-connected subway systems of urban areas (e.g., Seoul, Shanghai, Tokyo, and Singapore). Imagine a scenario, wherein a tourist is traveling around the city of, for instance, Seoul. There are various challenges to conquer, e.g., language barriers, information overload on Internet, and easy accessibility. However, the city of Seoul is well-connected through a public subway system, which can act as gateways for accessing relevant nearby information.

We propose that each subway station has a Bluetooth Low Energy (BLE) beacon, broadcasting its Global Location Number (GLN). A GLN is a GS1 ID key used for identification of locations, such as, subway stations, warehouses, and stores. Essentially, it is a 13-digit globally unique identifier and is fully compatible with International Organization for Standardization (ISO) standard 6523. In Fig. 8, we have shown two subway stations of Seoul, Hongik Univ. Station and Seoul Station, broadcasting their respective GLN identifiers through a BLE beacon. The GLN is utilized by user devices, such as, Smart Phone and Infotainment System, to obtain a list of services bounded with the identified location through a Naming Authority PoinTeR (NAPTR) query using Object Name Service (ONS). After obtaining the service list, the user device can access placeness service by using Representational State Transfer (REST) APIs (e.g., GET request) provided by GS1 Source, which is a GS1 standards-based Business-to-Consumer (B2C) framework for sharing information through digital channels.

An example user interaction flow is also shown in Fig. 8. Through a unified GS1Beacon application, a user can retrieve services associated with current location and access placeness service. Additionally, the whole system is open and flexible for application developers because of two reasons; firstly, ONS leverages the standard Domain Name System (DNS) infrastructure of the Internet, and secondly, the information from GS1 Source is accessible by using standardized REST APIs, therefore, application developers can create other innovative user interaction flows.

Next, we will discuss the components of Oliot, used for building Location Digest.

B. *GS1Beacon*

In our previous work [26], we proposed and evaluated GS1Beacon as a facilitator to connect an offline beacon device to its associated online service by using BLE technology. The beacon is installed in a physical location (e.g., a subway station) and periodically broadcasts advertising data. In the case of GS1Beacon, the advertising data is composed of GS1 ID keys. The reason for choosing GS1Beacon instead of other specifications, such as iBeacon (Apple), and Eddystone (Google) is because it is not bound to a specific service provider. The way GS1Beacon provides this layer of abstraction is by exploiting two GS1 standards: (1) GS1 ID keys [25], a globally unique set of identification keys for a comprehensive body of items and (2) GS1 ONS [27], a specification in tandem with DNS to locate authoritative services associated with a given GS1 ID key.

C. Object Name Service (ONS)

An ONS is a service lookup system, that uses the existing DNS infrastructure to locate authoritative services associated with a given GS1 ID key by implementing the Dynamic Delegation Discovery System (DDDS) algorithm [28]. The ONS lookup service receives Fully Qualified Domain Name (FQDN) as a query and responds back with a set of NAPTR records. The NAPTR records contain pointers to authoritative services associated with a given GS1 ID key. The conversion rules from a GS1 ID key to FQDN are outlined in GS1 ONS Standard [27], and are omitted here for brevity.

D. GS1 Source

GS1 Source [29] defines standard data and interfaces in the platform for communication of authentic and accurate product information. It is a federated system of distributed servers, binded together through ONS via lookup registry (GS1 Source Index). The interfaces of GS1 Source are shown in Fig. 9. Aggregator-Index Maintenance Interface (AIMI) defines an interface through which a Data Aggregator (DA) interacts with the GS1 Source Index to add, change, correct, or delete index entries that reference the DA. Aggregator-Index Query Interface (AIQI) defines the interface through which a DA queries the GS1 Source Index to obtain references of other DAs who may have data for the specified GS1 identifier. Aggregator-Aggregator Query Interface (AAQI) defines the interface through which one DA queries another for data of the specified GS1 identifier.

Listing 1: Sample GS1 Source data for placeness service

```
<?xml version="1.0" encoding="UTF-8"?>
<productData>
  <gln>08800026916024</gln>
  <targetMarket>410</targetMarket>
  <informationProviderGLN>
    8800026949145
  </informationProviderGLN>
  <informationProviderName>
    South Korea Tourism
  </informationProviderName>
  <avpList>
   <stringAVP name="locationName">
    Hongik Univ. Station
   </stringAVP>
  </avpList>
  <productDataRecord>
    <module>
      <basicProductInformationModule>
        <productName>Food</productName>
        <gpcCategoryCode>
          68040100
        </gpcCategoryCode>
        <imageLink>
          <url>http://example.com/food-image.jpg</url>
          <imageTypeCode>PRODUCT_IMAGE</imageTypeCode>
        </imageLink>
      </basicProductInformationModule>
      <basicProductInformationModule>
        ...
      </basicProductInformationModule>
    </module>
  </productDataRecord>
</productData>
```

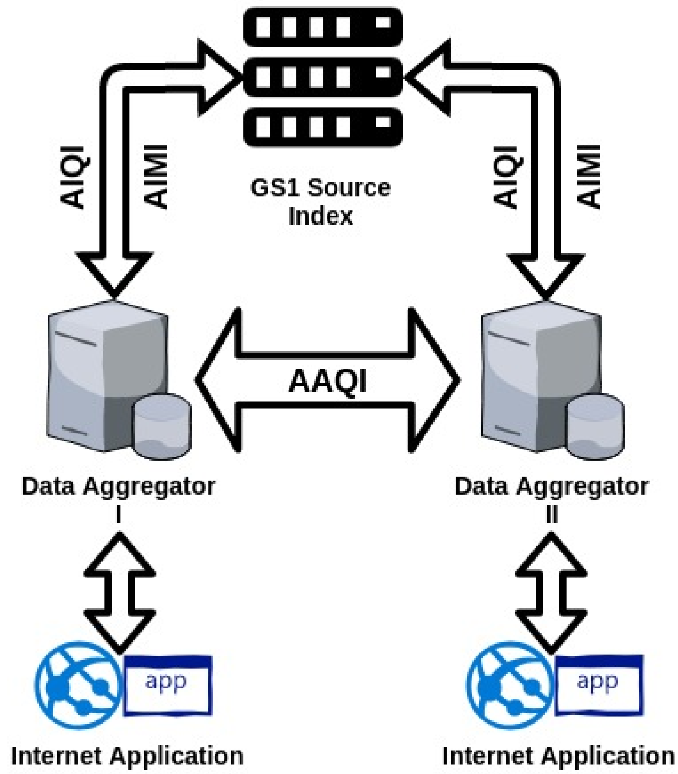

Fig. 9: GS1 Source Architecture: Internet applications interface with a Data Aggregator (DA) to access placeness service using REST APIs. DAs can query each other through AAQI after obtaining the reference from AIQI.

In our implementation, we adopt the standard interfaces and data definitions with a minor modification; instead of Global Trade Item Number (GTIN), identifier for products, we utilize GLN, the identifier for locations, as the GS1 ID key. However, this decision will not cause any conflict with other participants of the federated system, since the two identifiers are compatible in length with each other. GTIN has four variable length formats, i.e., GTIN-8 (8 digits), GTIN-12 (12 digits), GTIN-13 (13 digits), and GTIN-14 (14 digits), whereas, GLN is a fixed 13 digits format, which makes it compatible with GTIN-13. Additionally, Location Digest utilizes basicProductInformation module of the data specification for sharing image URLs of exemplar community experience as computed by placeness discovery mechanism discussed earlier. A sample data for the placeness service using GS1 Source is shown in Listing 1.

In the code listing, gln specifies the GLN of location (e.g., Hongik Univ. Station), informationProviderGLN specifies the GLN of information provider (e.g., South Korea Tourism), gpcCategoryCode specifies the Global Product Classification (e.g., Pre-Recorded or Digital Content Media), productName specifies the community experience label (e.g., Food, Drinks, and Ambiance), and imageLink specifies the URL of exemplary community experience. Although it is possible to specify multiple URLs and implement placeness as a ranked set of images, in this study we have restricted to only one image per community experience.

VI. Conclusion

Placeness plays a vital role in Smart City tourism. Owing to the ubiquitous availability of the Internet and mobile devices, geo-tagged data from social media platforms is increasingly playing an essential role in discovering placeness. In this work, we proposed *Location Digest*, a placeness service to find the exemplary community experience using social media.

Location Digest relies on a novel unsupervised mechanism to discover the various facets experienced by community members of an urban area and is implemented by using GS1 Global Standards-based open-source IoT platform to encourage interoperability. We believe that Location Digest will serve as an essential service for assisting tourists in a Smart City and enable them to make informed decisions.

As a future work, we will extend Location Digest to provide near real-time placeness attributes by using various sensors data from an urban area for discovering placeness. Furthermore, we will investigate methodologies for automatic labeling of placeness attributes and deploy a large-scale testbed.

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