Recommendations Based on Region and Spatial Profiles

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Abstract. Fuelled by the quantity of available online spatial data that continues to grow, the requirement for filtering spatial content to match mobile users' context becomes increasingly important. This paper introduces a flexible algorithm to derive users' preferences in a mobile and distributed system. Such preferences are implicitly computed from users' virtual and physical interactions with spatial features. Using this concept, region profiles for specific spatial contexts can be generated and used to recommend content to those visiting that region. Our approach provides a set of profiles (personal and region-based) which are combined to adapt the presentation of a given service to suit users' immediate needs and interests. A proposed college campus navigation assistant illustrates the benefits of such an unobtrusive recommender system.

Keywords: Location-based services, Contextual adaptation, Implicit profiling, Multi-user recommendations

1 Introduction

Due to the increase in the availability of online services which permit users to tag and edit spatial data as well as share location information, the quantity of available geo-information continues to grow. While there are many positive aspects to the availability of this information, including greater access to free spatial data and up-to-date information, there are also an increasing number of opportunities emerging in this domain. For example, information overload which is a well-known issue in the Web domain is now becoming prevalent among spatial data as the two are merged through Location-Based Services (LBS). In the Web domain a single search query can return millions of matching Web pages. Although most search engines order the returned results, it is still an ominous task for the user to search through these results as the semantics that emerge are not always those which are of interest. Similarly, the amount of information available via a LBS can be so voluminous that it makes finding relevant information difficult. This effect is particularly serious for LBS in which client tiers operate on mobile devices and therefore have reduced processing capabilities coupled with a smaller screen size on which to display information [4, 5]. Therefore, it is advantageous to only recommend a subset of data in this case. Of course this recommendation needs to be configured, so that the subset of data match the user preferences and interests while taking locational context into account.

This paper introduces a novel technique for generating user profiles within a LBS. By segmenting an environment into physical regions based on the underlying infrastructure topology, profiles for each region can be generated. This is achieved by amalgamating the individual profiles of those visiting such regions into a common region profile. LBS users are given the opportunity to determine which form of personalisation and recommendation (personal, collaborative or regional) suits their current needs. This technique is described by applying it to a case study of a college campus LBS assistant and highlights how this hybrid approach to profile generation can effectively resolve issues with comparable approaches.

The next section describes related work in the area of user profiling and shows how our work builds on this through the development of region profiles which resolve common problems with existing recommender systems. Section 3 presents the campus assistant LBS and highlights how profiling permits client-side adaptations and recommendations. Section 4 details clusters and group dynamic derivation, while section 5 describes the proposed profiling algorithm. A discussion of the limitations and on-going development of the approach are presented in section 6, while a summary of the work is provided in section 7.

2 User Profiling Methodologies

This section introduces user profiling techniques and describes their strengths and weaknesses as well as contexts where they have been applied. Our proposed technique and details of how it resolves inherent issues with existing approaches is also presented.

2.1 Profiling Techniques

Determining user preferences and defining profiles can be achieved using explicit or implicit techniques. The former involves directly querying the user for input regarding their interests. While this approach has the merit of an immediate set of interests, it can be time consuming, suffer from distortion and subjectivity while also distracting the user from the task at hand [18, 19]. Alternatively, implicit profiling involves monitors user behaviour and infers user interests. There are two main approaches used to implicitly derive a user profile and produce recommendations: content-based and collaborative.

The content-based approach for recommendation considers past actions of individuals as indicators of future behaviour. Individual analytical user profiling in the spatial domain has received attention lately; in particular such implicit profiling techniques have been employed to determine user interests when interacting with spatial content [11, 2]. In all cases, the information gleaned through such profiling is used to recommend a spatial content to the user. Amongst its advantages, this process has no additional overheads for the user. This method is favoured in many Web-based situations where interactions such as link clicking, bookmarking and printing are seen as an indication that the user is interested in the associated content [7]. Recently this methodology has been extended to the spatial context where interactions with map data act as interest indicators, permitting map personalisation [11]. While content-based recommendation is effective, there are several issues with this approach. In particular, the well-known *cold start period problem* is prevalent among such recommender systems. This period occurs when a new user profile is not fully defined and does not contain enough information to reliably infer user interests [15, 1]. Similarly, profiles generated by the content-based approach can also suffer from an *inertia of the content* related to the difficulty of measuring changes in rapidly changing behaviour [8].

Collaborative profiling approaches consider current actions and preferences of similar users as an indicator of one's own interests. Nowadays, this technique is a topic of interest in the spatial domain. As the use of LBS and the number of mobile users equipped with smart phones continues to grow, the ability to provide relevant group preferences to individuals is appealing. For example, [16] builds group profiles based on user interaction with map objects as well as geographic proximity to objects. Similarly, [6] use a location bias as the first step in performing collaborative recommendation. Such approaches are far less sensitive to the *inertia* of profile generation while also eliminating the *cold start* problem by associating a specific group profile to new users. However, using group profiles to define personal profiles can introduce *stereotypes of users* that satisfy users in general, but none of them in particular [13]. Furthermore it is difficult to formalise the notion of contextual proximity so that associations of users are neither too loose nor too restrictive, referred to as *grouping criterion*.

Both content-based and collaborative approaches have their merits and determining which one to use is not always clear. Hybrid methods can take the respective advantages of both techniques [1, 3]. The approach proposed in this paper extends a user profiling technique, which combines user mobility and interface interaction to infer interests [11]. Especially, these profiles are used to personalise services on a collaborative basis. This is achieved using implicit interest indicators, described in [10], combined with collaborative filtering and case-based reasoning [17], along with user location and context [12].

2.2 Proposed Approach

By introducing a region profile whereby all users contribute to, and take part of, a common and shared profile for specific geographical regions in which they interact, implicit profiling is improved. Unlike current group profiling techniques, different geographical regions assume a profile which is derived from the commonalities in the profiles of people visiting a specific spatial region. Accordingly, region profiles can be considered as a type of a group profile with a spatial context. It is however necessary to firstly ascertain individual user interests by monitoring their interactions with the device, information systems and physical locations. When visiting an area or spatial region, the contents of this profile, such as preferences, contribute to the profile for that spatial area. Simultaneously, recommendations are made to individual users considering their own profile and that of their current spatial context. Newcomers to the system, who have no profile can then be assigned the profile of the current spatial region that they are in before their own profile matures. Our algorithm envisions a multi-tiered LBS and provides different types of profile which resolve the problems of traditional implicit profiling as highlighted below:

- *Grouping criterion* : LBS is about getting the right information at the right place and time. That is how the execution space can be clustered along with the platform components giving rise to an almost natural "functionality-guided" grouping criterion.
- *Inertia of content* : as space is clustered, profiles can be broken apart and regularly updated whilst users move from one region to another.
- *Cold start* : group profiles can be derived locally for each LBS cluster, as long as different users join during the execution (but not necessarily at the same time). These profiles can be suggested to newcomers.
- *Stereotyped users* : as a user's experience in a cluster matures, their personal profile enriches and the initial suggested group profile has less and less impact.

3 Guiding scenario: the campus assistant

The proposed profiling methodology is exemplified by an illustrative case study involving students as they interact with facilities located on a college campus. This scenario involves students with wide-ranging interests. For example Jim is a new student discovering the campus, $John$ is already registered in Computer Science, and is interested in mathematics and engineering. $Jane$ is more interested in geography or history. Each would like to receive information that matches with their interests without demanding too much of their attention. These students' diverse interests are also reflected at the geographic level. The campus is divided into groups of buildings, each of them hosting one or several departments. For example, the humanities departments are co-located in the same building complex.

Our profiling methodology takes advantage of both user and geographic specialisations. First, the students are compared according to their location and nearby resources. Then their experience of the system is personalised according to their own preferences and to the preferences inferred by their current location

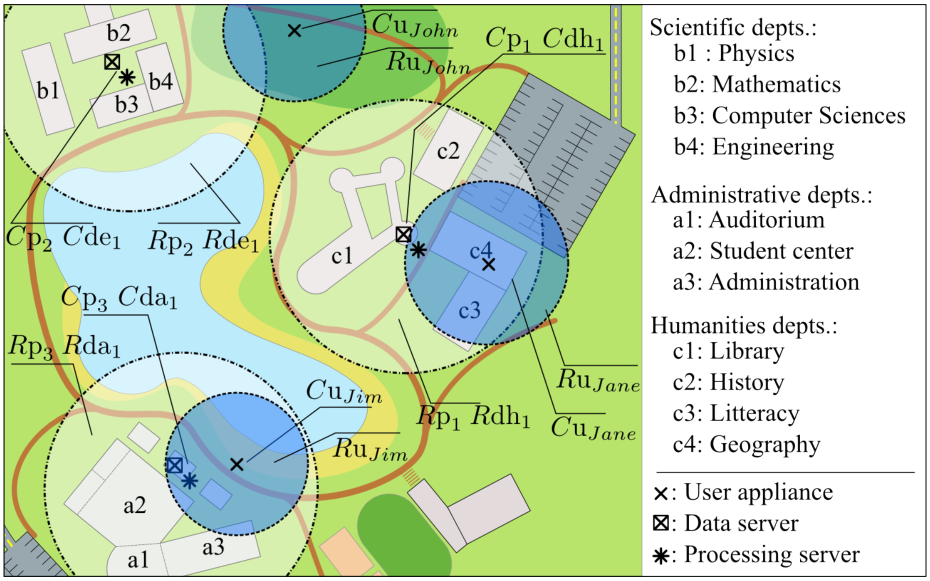


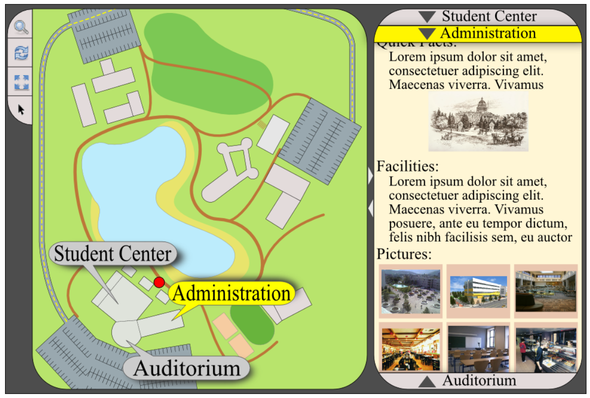
Fig. 1: Envisioned campus and service areas of the assistant information system at a given time instant t_1 of the execution

in the campus. Profiles are therefore likely to differ from one place to another, and from one user to another.

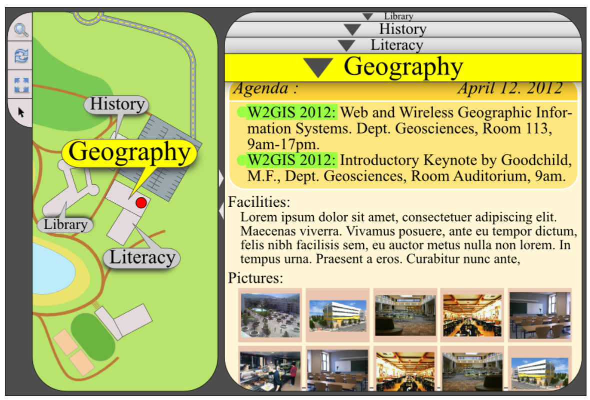
The campus assistant is designed so that several buildings and faculties provide service areas through WiFi hotspots (Fig. 1). These hotspots reflect the geographic clustering of the campus departments. Humanities, administrative and science areas have been defined. All service areas allow users to receive information regarding buildings in the surrounding area so that when a user is close to a particular building, they can obtain information about the departments located there. This approach, using geographical proximity to objects, is an initial step in a personalisation technique which contributes to the overall goal of reducing information overload.

Figure 2 displays examples of the proposed campus assistant on a mobile phone. On the left, the map panel highlights a user's current location and provides GIS functionality. The panel on the right details the currently selected element. Users can click on specific buildings and objects on the map to obtain additional information. Similarly, a user can click on the tabs within the panel to obtain information about other elements of the map. For example, as the user *Jim* (referred as $\mathrm{C}u_{Jim}$ in figure 1) walks through the "Administrative" area of service, he has access to information about the department and consults the central administration panel.

In the campus assistant, preference profiles are generated through interactions with content displayed and places visited. They are used to recommend spatial and non-spatial content to users [11]. As *Jim* is a new student he has



(a) *Jim*'s: Administrative Depts. interface, with no profile adaptation



(b) *Jane*'s: Humanities Depts. interface, with slight profile adaptations

Fig. 2: Sketches of the proposed campus assistant users interfaces at t_1

no profile and no preferences for content yet. While he waits at the university registration desk, he accesses the administrative service area, and all information he receives is displayed on an equal basis (Fig.2a). From previous use of the system, *Jane* already derived preferences regarding humanities related content. Her profile, among other things, indicates that she likes geography and that she usually displays information in a large frame. When *Jane* moves into the geography building based in the Humanities area, her display is adapted to emphasise geography-related information, and she receives notification of an upcoming conference (Fig. 2b). As she walks around the department, her profile is incorporated with that which exists for the humanities region.

At t_2, *Jim* also enters this spatial region, and his display adapts to the spatial profile for that region. In this case, it is derived from *Jane*'s profile as she is the only other individual that visited the humanities region. As $Jane's$ profile heavily recommends geography, this department appears high in the profile of the region and so Jim receives the same suggestion as $Jane$ regarding the conference. From now on, both $Jane$ and Jim contribute to the region profile. As $Jim's$ own interest for literacy begins to grow, their shared profile at the region level balances between literacy and geography.

At t_3, on her way to the science departments, $Jane$ leaves Jim to meet $John$, whose profile favours computer sciences and literacy. As they chat, their appliances share profiles. Specifically, $John's$ smart phone embeds $Jane's$ and $Jim's$ commonly derived humanities preferences, and $Jane's$ client downloads $John's$ science area profile.

Finally, at t_4, $John$ meets Jim in the humanities area. Although the profile he received from $Jane$ might have provided him with adapted content, $John$ prefers literacy. Therefore he rejects the profile he receives by cancelling the modification on his client and favours his own. By doing so, the conference event is not recommended to him. $John$ also strengthens the significance of literacy at the region profile level.

The above scenario effectively highlights the principles of how individual and region profiles operate in conjunction with each other to provide personalised recommendations for users of the system. The next sections formalise regions and profiles definitions in the context of the campus system. Details of how they are combined to provide different levels of personalisation are also outlined.

4 Clustering components of a location based system

This section describes a LBS as a set of hardware components. At any time of execution, the spatial union of these components (communication range) gives rise to region-based clusters defined by spatial, functional and related context.

4.1 Dynamic component and regions distribution

Multi-tiered systems such as the college campus assistant can be built upon a fluctuating set of active pieces of hardware. These components define the physical platform and assume several *functional roles* in the system. For example, multi-tier systems usually contain a user-interaction provider role, a data manager role, and a processing server role [9, 14]. These roles are implemented in one or several supporting components. For example, the user interaction components provide user-oriented views and interaction facilities; the data components import and export information subsets; and the processing components host data analysis and transformation functionality. The nature and number of roles are not limited but rather depend on how the system is modelled, and on the designers own choices. As a general rule, any components implementing identical tasks and/or hosting the same information belong to a same role.

Notation 1. Role and ID of a component: In the following, let $C{<}\mathrm{role}{>}_{id}$ denote a hardware component identified by “*id*” with respect to this component role, identified by “<role>”. When, at a given time instant t_i, this component is active within the system execution space, it belongs to the set $Platform(t_i) = \{C\mathrm{rla}_{id1}, C\mathrm{rla}_{id2}, \ldots, C\mathrm{rlx}_{idy}, \ldots, C\mathrm{rln}_{idm}\}$ of active components. Components belonging to this platform at t_i support distinct functional roles labelled as“rla”, “rlx”, “rln”, and at least two components, $C\mathrm{rla}_{id1}$ and $C\mathrm{rla}_{id2}$, implement the role rla.

In the campus assistant, raw information about groups of buildings are managed by dedicated data servers. Their roles “de”, “da” and “dh” have been chosen according to the content of the data they are hosting. For example, humanities information is broadcast by components associated to the role “dh” (Fig. 1($C\mathrm{dh}_1$)). Processing components are provided with raw data to generate tiled map views and layout the department information panels. As the processing and functionalities offered at their levels are identical, a unique role “p” has been defined and encompasses all three processing components (Fig. 1($C\mathrm{p}_{1\to 3}$)). At the infrastructure level, hardware components combine data management and processing facilities (Fig. 1(⊠✱)). Users have been assigned role “u”. Their clients, like $C\mathrm{u}_{Jim}$, constitute the uncertain piece of the platform, as a user's walk through the campus might make them available (or not) to the other components of the system.

Each component of $Platform(t_i)$ corresponds to a region that represents their accessibility range. Depending on the roles of their supporting components, several types of regions are distinguished. For example, 3-tier systems usually host: user-region(s) $R\mathrm{u}_i$, where the user(s) is/are located and interacts with the system; broadcasting region(s) $R\mathrm{d}_j$, where the information and data are available to the system; and processing region(s) $R\mathrm{p}_k$, where the tools and functionality for completing given tasks are available to the user.

Notation 2. Region of interest of a component: In the following, let $R{<}\mathrm{role}{>}_{id}$ denote the region of interest generated by component $C{<}\mathrm{role}{>}_{id}$. Such a region is an element of the set $Regions(t_i) = \{R\mathrm{rla}_{id1}, R\mathrm{rla}_{id2}, \ldots, R\mathrm{rlx}_{idy}, \ldots, R\mathrm{rln}_{idm}\}$. This set represents at t_i, the spatial extension of the multi-tiered architecture.

At the geographic level, a component region is defined at a given time by the area of influence and interaction of the component. Such limits can be derived from the communication and range capabilities of the hardware. For example, a standard WiFi transmission limits regions to within ≈50m from their supporting components. In another region definition, system designers can limit the access to hardware components to nearby locations, so that only the closest components can share resources. Such definitions induce a bi-directional connection between two hardware components when both components are included in the spatial range of the other. Components $C\mathrm{rla}_x$ and $C\mathrm{rlb}_y$ are said to be *related* and verify the equality $Related(C\mathrm{rla}_x, C\mathrm{rlb}_y, t_i) = 1$ when such two-way communication is possible. Inter-component relation based on communication capabilities induces that a given piece of hardware $C\mathrm{rla}_x$ is related to himself, and thus for all t_i, $Related(C\mathrm{rla}_x, C\mathrm{rla}_x, t_i) = 1$.

The set of active components gives rise to several spatial regions within the campus information system space. For example, at t_1, $Regions(t_1) = \{R\mathrm{u}_{Jim}, R\mathrm{u}_{John}, R\mathrm{u}_{Jane}, R\mathrm{p}_{1\to3}, R\mathrm{dh}_1, R\mathrm{da}_1, R\mathrm{de}_1\}$. In the campus assistant, the boundaries of the users' regions depend on the respective wireless capabilities of their mobile device. For example *Jim*'s, client's wireless access generates a region centred on $C\mathrm{u}_{Jim}$, and within which he interacts with the system. Processing and data handling components are paired as they are accessible through the same hotspots. At a spatial level, $R\mathrm{p}_{1\to3}$ and $R\mathrm{da}_1$, $R\mathrm{dh}_1$, $R\mathrm{de}_1$ respectively overlap. In contrast to the user regions, their boundaries have been purposely assigned so that the information about a group of buildings can only be accessed and processed nearby. For example, from his current location, *Jim* can only access information from the administrative departments. (Fig. 2a).

4.2 Clustering the components and grouping the users

In typical group-based recommender systems, components that share similar functionality, content and context, derive common preferences. The grouping criterion however depends on the system and might be difficult to model. With the proposed modelling approach of a LBS, the set of role-assigned components along with their regions provide an immediate criterion to a grouping process. In the following, a *cluster* is defined as a group of communicating components. More specifically, the *related* components at t_i form clusters, and a component $C\mathrm{rla}_x$ belongs to a cluster only when a component $C\mathrm{rlb}_y$ exists in this cluster so that $relate(C\mathrm{rla}_x, C\mathrm{rlb}_y, t_i) = 1$ is verified. As a component always relates to itself, the isolated components of the system derive single-element clusters. More formally, let $Cluster(\ldots)$ return at t_i the set of clustered components[4]:

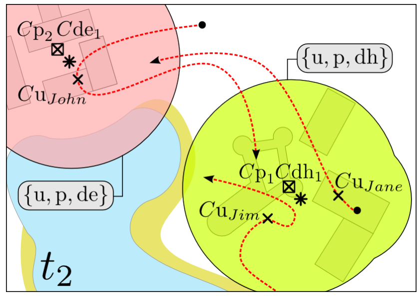
$$Cluster(t_k) = \bigcup_{\substack{C\mathrm{rla}_i \in \\ Platform(t_k)}} \big(Group(C\mathrm{rla}_i, \emptyset) - \emptyset\big)$$

with

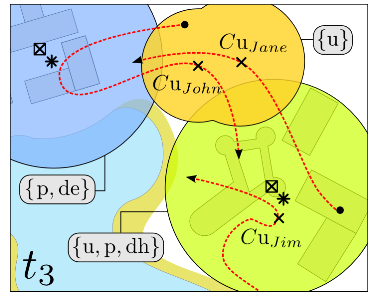
$$Group(C\mathrm{rla}_i, A) = \begin{Bmatrix} C\mathrm{rlb}_j \in Platform(t_k) \ \cup \ Group\big(C\mathrm{rlb}_j, A \cup \{C\mathrm{rlb}_j\}\big) \\ \mid \ Relate(C\mathrm{rla}_i, C\mathrm{rlb}_j, t_k) = 1 \ \wedge \ C\mathrm{rlb}_j \notin A \end{Bmatrix}$$

The individual boundaries of accessible components in the same cluster can be unified to highlight the spatial boundaries of a cluster. Figure 3 illustrates a configuration where cluster boundaries change as users move. For example, at time instant t_2, three clusters co-exists in the campus guide system, and $Cluster(t_2) = \big\{\{C\mathrm{u}_{John}, C\mathrm{p}_2, C\mathrm{de}_1\}, \{C\mathrm{u}_{Jane}, C\mathrm{u}_{Jim}, C\mathrm{p}_1, C\mathrm{dh}_1\}, \{C\mathrm{p}_3, C\mathrm{da}_1\}\big\}$. In the configuration depicted, *Jane* and *Jim* belong to a same cluster as they are both able to send and receive information from the humanities hotspot (Fig.3a).

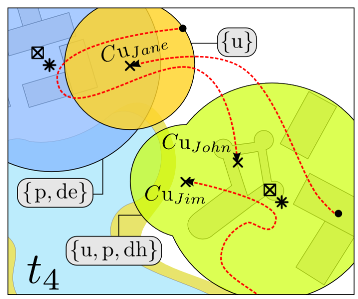
[4] $Cluster(\ldots)$ relies on a recursively defined $Group(\ldots)$ function. Given a component $C\mathrm{rla}_i$ and the empty set $A = \emptyset$ as an input, this function completes and returns A with the tree of related components accessible to $C\mathrm{rla}_i$.



(a)



(b)



(c)

Fig. 3: Footprints of the changing set of clusters from t_2 to t_4 (only the moving components are labelled; Administrative depts. cluster is not displayed).

When *Jane* moves towards the science departments, at some time between t_2 and t_3, $Relate(C\mathrm{u}_{Jim}, C\mathrm{u}_{Jane}, t_i \in]t_2, t_3[) = 0$, and her component opens a fourth, self-contained, cluster. At t_3, *John* meets *Jane*, their components exchange information, and $Relate(C\mathrm{u}_{John}, C\mathrm{u}_{Jane}, t_3) = 1$. At the cluster level, *John* joins *Jane's* newly created cluster (Fig. 3b). Again, the configuration changes at t_4 when *John* accesses the humanities hotspot and so now belongs to the cluster in green. Conversely, *Jim* loses his relationship with $C\mathrm{p}_1$ and $C\mathrm{dh}_1$ servers. However, thanks to a bridged connection through $C\mathrm{u}_{John}$, *Jim's* component is still part of the cluster in green (Fig. 3c).

Clusters need to be uniquely identified in order to be paired with preference profiles. A signature ID is given by the set of roles that the components in a cluster assume. For example, in figure 3, the green cluster signature is $\{\mathrm{u}, \mathrm{p}, \mathrm{dh}\}$ (i.e.: roles "user", "processing" and "data Humanities"), the users-only clusters are identified by the singleton $\{\mathrm{u}\}$ and $\{\mathrm{de}, \mathrm{p}\}$ label a cluster made of science department hotspot components without users.

Properties of clusters. With the objective of profiling user preferences and recommending content, the proposed spatial clustering induces the following properties:

- the components and the environmental context are shared among the users in a cluster;
- at the functional level, the data and tools offered to users are relative to each cluster.

Both properties by-pass the implicit profiling difficulty for grouping users, or components together in a recommender system (i.e.: *Grouping criterion* flaw). When users in a cluster contribute to a profile, they share a physical context and obtain access to the same subset of information and tools. Furthermore, the derivation of this grouping criterion occurs at no cost as users only need to identify neighbouring components corresponding to the cluster they belong to.

5 Profiling in a clustered system

This section details the content and make-up of spatial and user profiles. An algorithmic approach to profile derivation is also introduced. In our attempt to address the drawbacks of recommender systems, the definitions of profiles and the suggested algorithm complement cluster properties.

5.1 Content and types of profiles[5]

The proposed profiles combine the preferences of one or several users with respect to the content delivered and the functionality offered in a given cluster. To be more specific, a profile gathers an n-element set of ('key', scr) pairs, associated with a cluster signature [Clust. ID] and a component $C\mathrm{rla}_{idx}$ which this profile applies to. For example, the contents of an individual profile (IP) is given by:

$$IP^{\text{[Clust. ID]}}_{C\mathrm{rla}_{idx}} \rightarrow \big\{(\text{'key}_1\text{'}, scr_1), (\text{'key}_2\text{'}, scr_2), \ldots, (\text{'key}_i\text{'}, scr_i), \ldots, (\text{'key}_n\text{'}, scr_n)\big\}$$

The 'key' parts identify pieces of information or functionality that are available in a cluster with signature [Clust. ID], while scr scores quantify a user's (or group of users) interest towards the associated 'key' elements. In a profile, a pair of scores scr_a and scr_b verifying $scr_a > scr_b$ acknowledges a user's or group preferences for the information or functionality 'key$_a$' over 'key$_b$'. Such scores are float numbers in $[0, 1]$, so that their sum in a profile equals 1 (i.e.: $\sum_{i=1}^{n} scr_i = 1$).

Ordering user elements of interest by attributing scores, makes personalising the geospatial services possible. Personalisation in this case involves highlighting content relevant to the current users and hiding content which is not of interest to them. Similarly, the interface and functionality used to display and interact with the content can be adapted according to such preference profiles.

In the campus assistant $Jane's$ individual profile at t_1 highlights her interest for geography (Tab. 1a). $Jane's$ client consequently emphasises geography

[5] This section summarises the authors previous work, without detailing much of the actual profile content derivation. A complete description of personal profile derived from user's actions is given in [11].

Table 1: Contents of *Jane* personal profiles

(a) at t_1, within Humanities hostpot area	(b) at $t_i \in]t_2, t_3[$
$IP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{u}_{Jane}} \rightarrow \big\{$('Geog.', .4,), ('Libr.', .1), ('Hist., .2) ('Liter.', .2), ('InfoPane', .07), ('MapPane', .03)$\big\}$	$IP^{\{\mathrm{u}\}}_{C\mathrm{u}_{Jane}} \rightarrow \big\{$('InfoPane', .2), ('MapPane', .8)$\big\}$

related elements: the labels have been adapted, and the content panel automatically loads information about this department (Fig. 2b). The layout of the user interface also adapts to $Jane's$ current preference for descriptive content rather than a map. Conversely, $Jane's$ client infers her preference for campus mapping when she is alone between t_2 and t_3 (Tab. 1b). Accordingly, her client emphasises the map during this period.

The definition of profiles allows their contents to be easily mixed and average or historical profiles to be derived. This approach for constructing profiles discriminates several levels locally to each cluster:

- *individual profiles (IP)* gather the preferences and scores of a single user. At every time during execution, a client adapts its content and display to the individual profile of the current cluster. Table 1 provides examples of the content of such personal profiles;
- *immediate group profiles (IGP)* account for the averaged preferences of the users currently grouped in a cluster. Such profiles continually combine the individual profiles of users in a cluster on a per-value basis. The preferences depicted in group profiles reflect the most favoured content and functionality among the users;
- *strengthened group profiles (SGP)* balance the immediate group profiles with previously derived scores. For example, SGP at t_i averages the current immediate group profile and the previously derived SGP at t_{x-1}. These profiles are less sensitive to sudden variations of user preferences than immediate profiles.

For example, when Jim enters the humanities cluster at t_2, his component computes an immediate group profile $IGP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{u}_{Jim}}$ and subsequently adapts his user interface and content. Such profile derivation averages the individual profiles of all components in the cluster and can be summarised by the operation in fig. 4. Although the standard deviation of scores have been reduced by $Jim's$

$$
\begin{aligned}
&\big(IP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{u}_{Jane}} \rightarrow \big\{(\text{'Geog.'}, .4,), (\text{'Libr.'}, .1), (\text{'Hist.}, .2), (\text{'Liter.'}, .2), (\text{'InfoPane'}, .07), (\text{'MapPane'}, .03)\big\} \;+\\
&\;IP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{u}_{Jim}} \rightarrow \big\{(\text{'Geog.'}, .16,), (\text{'Libr.'}, .16), (\text{'Hist.}, .16), (\text{'Liter.'}, .16), (\text{'InfoPane'}, .16), (\text{'MapPane'}, .16)\big\}\\
&\;+IP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{dh}_1} \rightarrow \{\dots\} + IP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{p}_1} \rightarrow \{\dots\}\big)/4\\
=\;& IGP^{\{\mathrm{u,p,dh}\}}_{C\mathrm{p}_{jim}} \rightarrow \big\{(\text{'Geog.'}, .28,), (\text{'Libr.'}, .13), (\text{'Hist.}, .18), (\text{'Liter.'}, .18), (\text{'InfoPane'}, .12), (\text{'MapPane'}, .09)\big\}
\end{aligned}
$$

Fig. 4: Jim constitution of an immediate group profile at t_2

calibrated profile, the derived group profile still reflects $Jane's$ interest for geography. The server components also take part in the immediate group profile derivation. Their contribution depends on the sharing algorithm, detailed in the next section.

Profiles are stored by each component belonging to a cluster. Immediate and strengthened group profiles are identical for all components of the cluster. Individual profile scores differ on each client device, while they are equal at the server component level (i.e.: every score of a n-elements profile equals $1/n$). In the following $(IP|IGP|SGP)^{\text{[Clust. ID]}}_{C\text{rla}_{idx}}$ denotes the individual, immediate group, and strengthened group profiles of the component $C\text{rla}_{idx}$, locally in the cluster identified by [Clust. ID]

Properties of profiles. With regards to the usual recommender system drawbacks, different profile levels induce beneficial properties:

- users of the system are able to switch their active individual profile to either an immediate or strengthened group profile that are available in the cluster they belong to, whatever their adaptation policy is;
- profile choices can also be made automatically by the recommender system on a client device. For example, group profiles can be favoured only when a minimum number of users is reached;
- even when no other users currently belong to a cluster, a previous group profile should exist on one of the components when a newcomer enters a cluster.

Applying an individual profile is advantageous for a user who does not feel at ease with group preferences, and wants to avoid being *stereotyped*. New users are invited to adapt their content to a group profile; they therefore preserve themselves from a *cold start* period of undetermined preferences. Differences between IGP and SGP also help the recommender system to find the appropriate level of *content inertia*.

5.2 Maturing the profiles in a mobile system

The mobile nature of a LBS favours an additional solution to spread the preferences and avoid too much inertia in user profiles. Moving clients and servers can carry profiles constructed in distant clusters and share them in a peer-to-peer way. A set of components gathering in a cluster share not only profiles identified by this cluster but also any other profiles of different clusters they might have in common. Algorithm 1 summarises the proposed peer sharing methodology. This pseudo-code runs in a loop on each component of the system.

At first, a given component and their neighbouring devices exchange roles to identify the cluster they belong to (l.2). If necessary, IP, IGP and SGP profiles are allocated with all scores valued equally (l.3→5). Sharing and averaging scores occurs for all existing cluster IDs defined among the profiles allocated (l. 6). The sharing and merging procedure collects the personal profiles with ID [AnyClust] of the components in the current cluster and derives an averaged immediate profile as an output (l.7). In turn, the produced output combines to

Algorithm 1 Iterative profiles derivation at a given component $C\mathrm{rla}_{idx}$ level

1: **loop**
2: compute current cluster ID as [MyClust]
3: **if** ! $\left(IP^{[\mathrm{MyClust}]}_{C\mathrm{rla}_{idx}}\text{ allocated}\right)$ **then**
4: allocate equal profiles: $IP^{[\mathrm{MyClust}]}_{C\mathrm{rla}_{idx}}$, $IGP^{[\mathrm{MyClust}]}_{C\mathrm{rla}_{idx}}$, and $SGP^{[\mathrm{MyClust}]}_{C\mathrm{rla}_{idx}}$
5: **end if**
6: **for all** $\left(\text{individual profile } IP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}}\text{ allocated}\right)$ **do**
7: $IGP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}} \leftarrow ShareAndMerge\big([\mathrm{AnyClust}]\big)$
8: $SGP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}} \leftarrow Merge\big(IGP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}}, SGP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}}\big)$
9: **if** (Favour *Immediate group profile* policy) **then**
10: $IP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}} \leftarrow IGP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}}$
11: **else if** (Favour *Strengthened group profile* policy) **then**
12: $IP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}} \leftarrow SGP^{[\mathrm{AnyClust}]}_{C\mathrm{rla}_{idx}}$
13: **end if**
14: **end for**
15: *adapt*() $C\mathrm{rla}_{idx}$ to $IP^{[\mathrm{MyClust}]}_{C\mathrm{rla}_{idx}}$
16: $infer()$ preferences and scores until t_{x+1}
17: *update*() $IP^{[\mathrm{MyClust}]}_{C\mathrm{rla}_{idx}}$ with the infered scores
18: **end loop**

the last SGP profile and is stored as a newer version (l.8). Depending on the current component policy, the individual profile scores are updated to either IGP or SGP values; or are left unchanged (l.9→13). Lines 15 to 17 are built on existing work and is where the adaptation of the content presented, and the implicit perception of user preferences occur. The procedures *adapt*(), $infer()$ and *update*() have been defined in [11]. Overall, these functions act together as a recommender system on the client device: they infer preferences, complete the individual profile scores, and update the layout accordingly.

The profile sharing behaviour described in the case study are derived from the proposed algorithm. For example, at t_3, sharing profiles between $Jane$ and $John$ do not solely focus on their current user-only cluster (i.e.: with ID {u}), but also encompass the previously derived profiles they carry. Thanks to $Jane's$ experience of the system, $John's$ client embeds a humanities related IGP even if he stands outside of the boundaries of the humanities cluster. $John's$ decision not to adapt his content to this immediate group profile reflects a switch in his policy that favours personal instead of group profiles.

Properties of the sharing algorithm. The profile derivation algorithm encompasses typical features to improve preference sharing and recommendations in location-based services:

– profiles assigned to clusters are also shared outside of the cluster's context. The profiles of users can therefore be updated before they actually belong to a cluster;

– servers and user components are treated alike. Although preferences are not inferred and content is not adapted on servers, all the components of $Platform(t_i)$ share the profiles in a peer-to-peer approach.

Since the scores of any profile can be updated in every cluster, having a substantial number of components running the profile derivation algorithm is advisable to settle *inertia of profile content*. Due to the movement of components and interactions of devices, the content of profiles does not remain static for long.

6 Discussion

Recommender systems have been introduced as a solution to the increasing difficulty to sort and present relevant information to users of location-based services. In such systems, inferring preferences and adapting the content and interface is valuable to the user. Implicit as well as collaborative profilers sometimes fail to achieve this objective due to several technical and/or design drawbacks as mentioned in section 2. This paper highlights the properties of LBS that can resolve some profiling challenges for mobile systems. The concept has been implemented trough a prototype simulator. This tools allows different recommender system behaviours to be tested. This includes the modelling of different user mobility (with pauses) as well as different interaction modes based on mouse tracking. The simulator generates group profiles that can produce adapted interfaces and allows for comparison between variations of different profiles.

Table 2: Summary of the proposed improvement sources with regard to the usual challenges a recommender system faces

	Grouping criterion	*Inertia of content*	*Cold start*	*Stereotyped users*
Regional clustering	components undergo a same functional and environmental context	-	-	-
	low-resources signatures derivation			
Profile nature and content	-	profiles types IGP and SGP differ by their content inertia	ready to use profiles when entering a cluster	user or system policy to adapt to the most appropriate type.
Sharing algorithm	-	clusters profiles are shared outside of their boundaries	-	-
		each component produces and shares profiles		

The proposed approach models a LBS as a set of regions whose relationships give rise to clusters of active users and components. Profiles are built locally for each cluster and rank the data and functionality offered within a cluster. Several types of profiles, either personal or group-based, have been introduced. Depending on their experience of the system, users can switch from one type to another and find the profile that best suits their preferences. An algorithm to share and merge profiles across the system space benefits from user and component mobility and enriches profiles with up-to-date content scores. Clusters, profile descriptions, and sharing algorithms constitute distinct layers that together improve traditional recommender systems. Several properties have been explored in the paper and are summarised in table 2.

The potential positive properties of our hybrid approach can be discussed and raise additional open questions. While one of the main benefits of the approach, is the ability to provide different types of profiles, which may improve the *inertia* and *cold start* issues, these are not terms or concepts familiar to average users. As a result, inexperienced users may not alternate between profiles, choosing to remain with the default one. A challenge is therefore, to inform users on when to switch profiles and the benefits this can bring to their interaction with the system. This can be achieved at the interface level by providing information about the contents of other types of profile.

In the system described here, the cluster arrangement is preconfigured based on the underlying computer network infrastructure. In the case of the campus navigation assistant, this corresponds to the physical layout of the buildings. Generating such clusters creates an overhead for the developer and system designer. It would be more advantageous for the cluster arrangement to form naturally based on the underlying infrastructure. The implementation of this would enable a generic system to be developed and used in various contexts.

Many of the limitations discussed above can be alleviated through further development of the approach and refinement of the algorithms. For example, fine tuning of the algorithm for assigning weights to preferences within profiles can improve the recommendations returned to users. Generally, such details are dependent on the specific context of use which must be taken into consideration. Technical details on how devices share profiles also needs to be investigated. The approach described here is robust and can be broadened to not only include places or regions visited within the context of a small geographical area, like a campus for example, but also for wider interactions. As people share more and more location-based information through social interaction and networks, this data can be used to produce region profiles on a national and international level.

7 Conclusion

This paper has introduced a new type of profile, the region profile, which offers an innovative technique for personalising location-based services. Individual user profiles are generated by monitoring user interactions with the physical environment and online content. These robust profiling techniques can be used to produce relevant recommendations at the interface level. To solve issues with recommender systems, such as the well-known *cold start* and *inertia* problems, region profiles are introduced. Regions of interest are generated by the components of an underlying distributed infrastructure. The individual profiles of users entering such regions get combined to create a profile for that region. This emerging region profile then contributes to individual recommendations and profiles. By empowering the user with the possibility of using their personal profile, that of the region or a hybrid, appropriate recommendations can be delivered from a user's first interaction with the system. A case-study of a college campus is provided to illustrate the approach. Work on refining the algorithms and the technical details of how profiles are shared is ongoing.

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