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Challenges in Context-Aware Mobile Language Learning: the MASELTOV Approach

Mark Gaved^{1*}, Patrick Luley², Sofoklis Efremidis³, Iakovos Georgiou³, Agnes Kukulska-Hulme¹, Ann Jones¹, and Eileen Scanlon¹

¹ The Open University, Milton Keynes, United Kingdom
(mark.gaved, agnes.kukulska-hulme, ann.jones, eileen.scanlon)@open.ac.uk

² DIGITAL, Joanneum Research Forschungsgesellschaft mbH, Graz, Austria
patrick.luley@joanneum.at

³ Athens Information Technology, Athens, Greece
(sefr, iage)@ait.gr

Abstract. Smartphones, as highly portable networked computing devices with embedded sensors including GPS receivers, are ideal platforms to support context-aware language learning. They can enable learning when the user is engaged in everyday activities while out and about, complementing formal language classes. A significant challenge, however, has been the practical implementation of services that can accurately identify and make use of context, particularly location, to offer meaningful language learning recommendations to users. In this paper we review a range of approaches to identifying context to support mobile language learning. We consider how dynamically changing aspects of context may influence the quality of recommendations presented to a user. We introduce the MASELTOV project’s use of context awareness combined with a rules-based recommendation engine to present suitable learning content to recent immigrants in urban areas; a group that may benefit from contextual support and can use the city as a learning environment.

Keywords: context-aware learning, language learning, location-based learning, recommender systems, immigration, urban informatics

1 Introduction

Smartphones enable context-aware learning – real-world support that takes into account the learner’s present and historical preferences, learning activities and places visited – on devices that many people use daily. Smartphones have sensors that can capture location and activity, they have network connectivity to enable interaction, and they have the computing power to manage learning activities. Context plays an important role in language learning, and context-aware technologies have been identified as potentially enhancing language learning [1]. Context refers to a number of parameters that may affect learning, and inform the selection of relevant resources to support a learner “including location, social activity and learning goals” [2, p. 4].

Lave and Wenger [3] argue knowledge is best gained in the situation in which it is to be employed, and since language use is typically social, enabling communication with fellow learners and native speakers is important.

This paper reviews approaches to context-aware mobile language learning, and introduces the MASELTOV approach: exploring how contextually aware language learning could be used to support recent immigrants to Europe to help them with social inclusion. MASELTOV, an EU FP7 funded project (<http://www.maseltoev.eu>), is considering how a system could support learners in a city-wide landscape, operating at scale (across a large area and potentially thousands of users), and applied to any urban area in Europe. Our target audience has a limited educational background and likely to have work and family commitments that will make attending formal educational classes difficult; therefore a smartphone based service which can be accessed anywhere and make use of the lived environment as a contextual resource is particularly suited to this group. In the MASELTOV project, the concept of the learner's location triggering activity is important, in particular how the services can support incidental learning, "unintentional or unplanned learning that results from other activities" [4, p.1]. An Incidental Learning Framework was produced to analyse mobile incidental learning in detail and to facilitate the communication of learning designs appropriate to the situation in which an immigrant wishes to use the service [5]. The Framework considers the place an incident occurs, task(s) the learner is carrying out, the tools the learner uses, the social support that the learner makes use of, the learning outcomes to be achieved and the (relative) time the incidental learning occurs.

To achieve the goals of language learning and social inclusion, MASELTOV is building a number of integrated mobile apps, under a single dashboard (the MApp) that our target audience can use in their daily activities to both resolve immediate needs and also to enable reflection and further planning of learning goals. The MApp includes the following services:

- Language learning activities: focused around key inclusion challenges such as employment, healthcare, and negotiating bureaucracy
- TextLens: converts images taken with the phone's camera to text, and translates them using a third party translation tool or onboard dictionary
- Navigation tools: public transport planning and pedestrian sat-nav
- Help radar: finds nearby volunteers to help the user solve immediate problems
- Places of interest service: listing places of interest in the city
- Serious game: providing playful learning about cultural differences
- Information service: information about services in the new city e.g. health, employment
- Social tools: to enable contact with other learners, and sharing knowledge
- Context awareness service to make sense of users' activities
- User Profile to store user preferences, records of activities, show usage statistics and display progress indicators
- A Recommender system to provide contextually relevant targeted and personalized recommendations, including learning resources

The MASELTOV system uses mobile phone sensors and user inputs to establish context, and interrogates data collected by these services with a recommendation engine to provide relevant prompts for immediate or future learning. By drawing on user activity across a number of widely differing services, and multiple attributes of context, the MASELTOV system aims to provide highly relevant learning resources. By offering users a number of ways of improving their knowledge and understanding of the target language and culture, the system offers flexible and personalized learning that also takes account of the local environment and people as learning resources.

In this paper we consider five key contextual aspects (location; mode of activity; history of activities; social interactions; and learning goals and personal interests) and report on how the MASELTOV project addresses each, and how, through the use of a contextually aware service, recommendation engine and a user profile, they support contextually aware language learning. We conclude by discussing outstanding challenges and future work.

2 Location

Early work in context-aware computing identified location as a key aspect to providing relevant resources to users, e.g. Abowd et al.'s conceptualisation of a tour guide [6]. The development of smartphones with affordable and compact embedded sensors in the last decade has made such theoretical tools a reality. Approaches can be divided into those that 'automatically' identify location by the use of sensors built into the phone, and those that require manual input from the smartphone user.

2.1 Location Identified Through Automated Input

Most smartphones can calculate geographical position using onboard sensors. Location can be calculated in a number of ways:

- GNSS receivers: calculating location from satellite transmissions, often using the US GPS (Global Positioning System). They can often identify location when outside to approximately 5-10 metres, but can be affected by large buildings and offer poorer quality accuracy where there is less satellite coverage.
- WiFi access points: location can be calculated from the comparative signal strength of nearby WiFi access points with known geographical coordinates, "WiFi fingerprinting". This can give accuracy at around 30m when used in urban areas where there is a sufficient density of WiFi networks, and requires internet connectivity.
- Cell phone tower signals: triangulating location based on signal strength of nearby mobile phone towers. However, this method only identifies location to approximately 300m accuracy in urban areas (less in rural areas due to lower coverage).
- Inertial Measurement Units: smartphone build-in sensors capable of measuring motion as well as orientation. Given a starting position, the subsequent locations can be iterated e.g. by step length and step frequency detection or double integra-

tion of the determined acceleration. This approach is also known as Dead Reckoning (DR) and stays stable within up to 1 metre for a 100 metre distance travelled.

- **Transponder Beacons:** dedicated transmitters which are sending a periodic beacon signal based on the Bluetooth Low Energy profile. The transponders have to be installed on site prior to location measurements. Position can be determined by either trilateration or fingerprinting (identifying the transponders by unique information they provide). Depending on deployment granularity provides accuracy between 70 to 0.1 metres.

In some cases, more than one of these methods is used in combination to increase the accuracy of position sensing.

Other services are also required to enable meaningful interpretation of the location identified, often provided as a series of geographical coordinates, such as a map service to show where the user is, or a database of Places Of Interest (POIs), to show what significant places are near to where the user is currently located. These services might be stored on the smartphone, or on remote servers (e.g. Google Maps) and in the latter case require a network connection. With some services users can download resources (like local maps) while connected, for later offline use.

The LOCH system [7] enabled Japanese learners to carry out practical tasks in a typical everyday environment such as asking for information at a train station. GPS receivers were used to identify location, and based on this information, remote tutors would offer location-specific feedback. Similarly, the PALLAS system, designed for language learners' interest-based informal learning around a city uses GPS to identify position and recommend relevant places of potential interest [8]. Zhou and Rechert's prototype personalized e-learning system for use in a botanical garden draws on both WiFi and GPS positioning to establish the learner's location, and position of nearby plants of probable interest [9]. In the MASELTOV app, we identify location through the "Android Location API" which uses a combination of GPS, WiFi fingerprinting and cell tower positioning.

2.2 Location Identified Through Manual Input

Location may be identified by the learner manually engaging with the environment, or with their phone. Markers can be placed on objects or locations in the physical environment, and taking a photo or otherwise scanning these with the phone can capture information, such as coordinates or a URL that can then access information from a remote server. For example, the KLIV project [10] enabled nurses to scan barcodes on equipment in an intensive care unit to be successfully instructed on their use. Ogata and Yano's JALEPAS system for learning the correct forms of politely addressing other people in Japanese [1] used RFID tags fixed to doorways when indoors to understand when a learner entered a particular room and scanned the tags, which could then trigger corresponding appropriate content objects to indicate position.

These approaches require the prior 'marking up' of locations, to ensure that the necessary tags are in place in all the likely locations learners might visit. While this

can work for small and controlled study areas, there is a challenge of scalability if a larger area such as a whole city is to be the environment where context aware learning may be triggered.

A different approach is taken in Edge et al.'s 'MicroMandarin' language learning system [11] which makes use of an existing social network service, the popular Foursquare app (<http://www.foursquare.com>), to confirm the user's current physical location and likely activity. The MicroMandarin service takes the information about the Foursquare location chosen by a learner to offer context-relevant small learning resources. If a user checks into a location that has been previously recorded as a café by Foursquare, the MicroMandarin service will offer vocabulary resources based on dining, such as the name of common café choices, paying for orders, etc. Linking through to social networks also enables the learner to access an existing community and draw upon their resources.

As MASELTOV seeks to provide a service that can support users across whole cities, the prior marking of locations is not an approach that we consider achievable, and similarly, reliance on third party locational services (e.g. Foursquare) may only give limited coverage. Furthermore, we want to make the service as easy to use as possible, and hence not require users to manually identify their location before being able to provide locational services. Even places like home and work are identified automatically by analysing daily routines. For this reason our approach is to identify location 'automatically' rather than via user input, deriving data from sensors onboard the smartphone. While this currently limits accuracy, advances in technology are likely to continue to improve accuracy rapidly over the next few years, for example with systems achieving greater accuracy by triangulating data from different GNSS systems (GPS, the Russian GLONASS, and the soon to appear European GALILEO).

3 Mode of Activity

The user's current mode of activity can provide contextual information which indicates which resources may be appropriate to offer to a learner, or the best times to provide resources. Like locational data, this can either be automatically derived from a smartphone's sensors (e.g. accelerometers), or by the user entering their activity manually (e.g. from a menu). Bristow et al. [12] identified that body position (e.g. sitting, standing, or walking) was key in defining the user's context when considering what resources to recommend to them, and used accelerometers to calculate this information.

The MASELTOV system has an activity recognition module which collects data from sensors built into the smartphone (movement and tilting) and interprets these to understand when the user is walking, is in a vehicle, or idle. This information is passed to the user profile, and adds contextual information to enable a better recommendation of learning resources: for example, a user who has been stationary for a period of time might be interested to receive a recommendation to try a language learning activity, while a user who is moving rapidly is not so likely to be receptive to an immediate recommendation, but might be interested to check later. Furthermore,

the mode of activity also includes the recognition of different kinds of transportation like riding a bike, driving a car or using public transport. This knowledge is also shared with the user profile to learn about users' daily behaviours in order to recommend learning content on public transport or different kinds of vehicles.

4 History of Users' Activity

Return visits to locations, or other repeated activities can provide contextual information that can trigger learning resources: if a learner frequently visits a place we might assume it has some significance to them. Like the MOBIlearn project, we see "context as a *dynamic process with historical dependencies*" [13, p. 116]. A user's previous activities and choices can provide contextual information as well as their current actions.

For example, frequent visits to a train station might result in a recommendation to learn language about the public transport system and repeated visits might lead to different material being offered. The MOBIlearn project recognised that context included historical interactions as well as an interpretation of the current, dynamically changing information: resources provided to someone visiting a museum for the fourth time might not be as suitable as for someone's initial visit [14].

Another example is the SCROLL system [15] that stores a learner's images and text notes to remind them of what language lessons they have learned in a real life situation (such as seeing a doctor in the hospital), and associates these notes with locational data from the GPS receiver. On revisiting the location, the previous visits' notes are presented to the user, to remind them of what they learnt before, encourage consolidation and further learning.

Determining which elements of the environmental data are relevant and most important for informing the learner's goals is a significant challenge, as some data passed to a user profile may be of little importance to the learner. This is highly problematic in busy urban environments where there may be many places of interest nearby, and there are large amounts of contextual information that can potentially be gathered. Cui and Bull's TenseITS system [16] considered this challenge and included historical, cumulative preferences so that the user could register their context manually, to enable the system to infer what materials would be most appropriate for the learner. Learners could enter information about where they were, their current concentration level (e.g. high or low), how much time they had available, and how often they were likely to be interrupted.

The MASELTOV user profile (described in more detail below) records both user preferences, and also historical activity to enable more accurate contextual recommendations.

5 Social Interactions

Social interaction is critical for language learning [17], and smartphones which can connect learners to peers may encourage interaction with other learners and natives in

authentic environments, enabling learners to “co-construct knowledge to solve problems and fill information gaps” [18, p. 283].

Recommender systems have used records of social interactions to help inform further recommendations, such as the 3a system [19]. Specific services may encourage social interactions, for example the PERKAM prototype that enables learners to find relevant peer learner-helpers [20].

The MASELTOV app has two explicit social tools: a forum, that allows users to share learning experiences, contact other learners, and socialise; and the geo-social radar, which enables them to identify local volunteers who may be able to help resolve a specific problem (such as translating at a local government office to resolve a bureaucratic need). The language learning activities also include social interactions: tasks are set that encourage the learner to interact with native speakers, and also to post small texts on the MASELTOV forum and get feedback from other learners. Furthermore, the TextLens tool allows users to upload images they have captured to social spaces, to get help for understanding their meaning. MASELTOV captures social activity through two methods: capturing usage of the relevant tools (forum, language learning activities, and geo-social radar), and a social interaction detection module, which, with the users’ explicit permission, can generate anonymous statistics on communication behaviour including phone calls and typed text messages. This contextual information might identify appropriate times to prompt users to try a learning activity, or encourage them to further participate in socially-focused learning activities: for example, if little use of the forum is identified.

6 Learning Goals and Personal Interests

Brown et al. [2] identify learning goals as providing important data for context-aware learning systems. Recommendations for learning resources that aim to support daily living, rather than the completion of a structured curriculum need to take into account personal goals and interests as well as providing resources appropriate to the learner’s current level of learning competency and progress through materials. The PERKAM system, for example, identifies personal interests through a learner profile: on registration, learners are asked to enter their personal information and topics of interest, and as they engage with the system, their actions are also recorded to the profile [20].

The MASELTOV service, which aims to support immigrants learning through their daily activities, and motivate an audience which might have limited or poor prior experiences of formal education, takes into account their personal interests and activities to provide relevant learning content. The MASELTOV system asks users to set up a user profile when initially registering, indicating their preferences and interests. While all fields are optional (to allow a user to take advantage of the MASELTOV services yet remain as anonymous as they wish), the user is informed that providing preferences will help improve recommendations for learning resources. This information is combined with the history of activities described previously and similarly reported to the user profile, in order to improve the quality of recommendations. On

the production of recommendations, users are asked to rate their quality to enable better defined future recommendations. Future versions of the MASELTOV system will also enable learners to indicate their learning goals, and match recommendations against these ambitions.

7 The MASELTOV Approach to the Challenges of Context-Aware Learning

In MASELTOV we provide contextually aware language learning services through: (1) the use of sensors (e.g. GPS, accelerometers), (2) a number of services that generate context aware information, (3) the user's profile to store users' identities, preferences and records of activity, and (4) a recommendation service that analyses contextual information and produces meaningful recommendations. We have described the use of sensors above, and will now turn to describe our context aware service, and the user profile and recommendation services.

7.1 Context Aware Service

The context recognition service is designed to run locally on the user's smartphone as a ubiquitous background service implemented for the mobile multisensory interpretation of user behavior, as a foundation to support immigrants in host urban environments. This module within the MASELTOV app enables filtering of relevant context information, and provides the background data for language learning recommendations based on the situation-dependent context of the user's environment.

A geo-contextual event analysis sub-module incorporates geographic information of the user's surrounding environment. The geographic information facilitates recommendations connected to places visited and places that are of special interest to a user. If the MASELTOV system detects that the user is near a specific place, common phrases for predicted communication scenarios (i.e. at the doctor, at the supermarket, etc.) or instructions for proper behaviour/communication specific for this kind of place can be provided. The module provides a collection of identified interests as well, which is deduced from geo-contextual analyses and can be used to deliver highly relevant language learning lessons only, which are strongly connected to real situations faced during the day. The knowledge about the current state of movement of users can be used to improve the acceptance of recommendations for a user, e.g. to determine the proper moment to send information to the user by detecting idle or high activity periods.

It should be noted that the user's context is a wider notion and encompasses information in addition to the user's geolocation. For example, information that is searched, or a topic that is discussed in a forum defines additional contextual information pertaining to the current interests of the user. Such contextual information can also form the basis for generating targeted recommendations for learning.

7.2 User Profile

In MASELTOV, a User Profile is used to store the learner's personal preferences and a history of their actions and activities, in order to inform recommendations for learning resources. On registering, the learner enters their basic profile including their personal information, interests and competencies. As they engage with MASELTOV services, e.g. search for a place of interest, or complete a language lesson, their usage and progress is recorded. If they have agreed to have their location tracked the context aware services will report their journeys and interpret their mode of activity to the user profile. This data forms the basis of the information used to present the user with recommendations for learning resources.

7.3 Recommendation Service

A context aware learning system requires a service that will provide relevant content to the user based on the contextual cues it has been given. Recommender systems for technology enhanced learning offer "some specific characteristics that are not met by today's general purpose recommendation approaches" [21, p. 319] particularly that each learner has their own learning path, and may be using their own preferred combination of tools in different environments. Traditional recommendation systems draw from two types of entities: users, and items. The majority of TEL based systems rely on contextual information drawn from personal profiles and learning progress, and do not draw on locational or activity based contextual information (*ibid.*). Wanaskar et al. [22] distinguish recommender systems as falling into one of two major categories: collaborative recommendation systems, and content based recommendation systems. In collaborative filtering systems a user is recommended items based on the past ratings of all users collectively; whereas in content-based recommending systems, a user is recommended items that are similar in content to items the user has liked in the past, or matched to attributes of the user. Melville and Sindhvani [23] identify that the two approaches can be combined to form a hybrid approach. The approach taken by the MASELTOV system is to employ a rule based recommender system.

Underpinning such a system is needed to interpret contextual data; this is achieved in MASELTOV by employing a rule based system as noted above. Such systems take as input a set of rules of the form precondition \rightarrow action, as well as a set of data and produce their recommendations in three phases [24]:

1. Data collection – data on the user's interests and activities must be collected and combined to provide information for the recommendation system
2. Pattern discovery – rules (a number of conditions) are applied to the collected information. If a match occurs, then a recommendation might be triggered. Alternatively, the information might activate a different rule or bring a rule closer to being triggered
3. Recommendation – when the conditions of a rule are met a recommendation (action) is generated and sent to the user, suggesting an action they can take or a link to some resources they may use.

Zaldivar et al. [25] explain how rules can offer specific recommendations with even no usage information but caution that that large rule sets are hard to maintain, reengineer, and adapt to user preferences.

All the services in the MASELTOV app send information ('events') periodically when they are used to the learner's user profile on a remote server. These events are temporarily stored on the smartphone if a network connection is not available. As soon as the smartphone goes online again, the events are sent to the backend server where the recommender system is running and checked to see if they match a rule and trigger a recommendation, or contribute towards moving a rule towards being triggered. If a recommendation is produced then the recommender system will send this to the user's smartphone as a notification (similar to a text message notification) for the user to read at their convenience, and follow to the recommender learning resources.

A range of recommendations are triggered by the MASELTOV system, including:

- Contextually suitable resources: identifying a user's location may result in a recommendation to visit a nearby place, or try a language learning activity associated with categories of places they are near to (e.g. healthcare, transport).
- Progress in a task: achieving a higher level of language competency (identified by completing language lessons and associated assessment) may trigger a competency-related activity
- Identifying complementary services: encouraging learners to try services that may support their activities. For example, if a learner is using the TextLens service to photograph notices in a doctor's surgery to understand medical services, they may be encouraged to share the images with fellow learners on the MASELTOV forum, or in a dedicated Facebook learners' group.
- Recognising inactivity: if a learner has not used a particular service, or starts to use a service then stops using it, they may be encouraged to try using it again (a common strategy employed by online learning environments like Khan Academy, or busuu).

Some recommendations are time-critical: suggesting that a user may like to visit a nearby place of a type they are interested in is only valid as long as they are within a certain distance of the place, so rules can include the concept of expiration. If somebody has moved elsewhere, or their phone has been switched off and a recommendation can't be sent, then it may be deleted and not sent forward to the user. However this information (being near a place) is still stored in the User Profile as it may be useful for another rule: noting that a person regularly visits train stations may trigger a recommendation to suggest some language activities around travelling on public transport. Even though the learner is not at the train station at the time, they may wish to view their recommendations when at home, when they have time to follow up the learning suggestions.

Learners are asked to provide feedback on the value of the recommendations they are sent (selecting or rejecting them), and this information is stored in the user profile to help further improve the quality of future recommendations. However, this creates the challenge of requiring the system to understand why a recommendation may have

been rejected. For example, the user might no longer be interested in a domain they have selected (e.g. restaurants), and a follow-up question needs be sent to the user e.g. “Do you still want to get recommendations for restaurants?” Alternatively, the user may not really be interested in this specific recommendation (a particular restaurant), but is still interested in the general category, and can be asked to provide further detail (they may not like a particular restaurant, or prefer Italian restaurants to French restaurants).

8 Challenges

Contextually aware language learning is becoming a reality with the rapid development of smartphones, and their increasing availability to the public. However, there are still outstanding challenges to be addressed:

- Identifying location accurately: the majority of sensor based approaches (e.g. deriving location from GPS data) do not offer enough accuracy to distinguish the users’ focus when there are multiple points of potential interest in close proximity and could lead to very different recommendations, some of which will be seen as irrelevant. Additionally, geographical data systems such as OpenStreetMap that are employed by recommender systems to indicate points of interest based on locational data may not provide enough detail or be comprehensive enough in their coverage to provide accurate recommendations. Identification of location via pre-populated markers may give greater confidence in establishing the user’s preferred focus, but faces the challenge of scalability across large areas.
- Timely recommendations: it is important that recommendations to users are given whilst they are still relevant (e.g. current location, mode of activity, or progression through learning materials). Recommendations that are no longer appropriate to the user’s context may be seen as irrelevant and a distraction. If the system relies on passing contextual information to a remote server to generate the recommendations, environments where network connectivity cannot be assured may mean recommendations are delivered too late to be of use. The recommendations that are produced by the MASELTOV recommender have an optional expiration tag. An expired recommendation is no longer presented to the user. Recommendations may expire at an absolute time (e.g., Jan 25, 20:30), at a relative time (e.g., 20 minutes from now), or upon the reception of an event.
- The overhead of defining and keeping rules up-to-date for a rules-based recommendation system. Defining rules is a complex task, and needs domain experts (e.g. language teachers) rather than programmers to create and update rules. This implies the requirement for an authoring interface that is usable by domain experts, and not just the programmers who are building the underlying software systems.
- Ethical issues of tracking users’ activities and locations: users may be concerned about how their contextual information is stored or who has access to it, and how it may be used. Contextually aware language learning systems must inform users clearly how their data will be used and stored, and offer the opportunity to opt out of some or all data gathering (though users will need to understand this may reduce

the quality of recommendations that can be made to them). The User Profile component of the MASELTOV platform gives the user the option to switch on and off the collection of a number of contextual parameters, thus placing the user at control for what information he/she allows to be collected.

- Enabling smartphone users to shift from using their smartphone as purely a communication and entertainment device to exploiting it for learning. This conceptual shift will be facilitated by teachers or mentors encouraging learners to use services such as the MApp for specific learning activities.
- Extending a context-based learning experience into a more prolonged or reflective learning experience over time. This may be achieved through application designs by prompting learners to continue learning or revisit past learning.
- Overcoming various barriers to learners practicing just-in-time oral language skills on the phone in public. Some speaking practice could be designed so that it mimics natural phone conversations.

9 Conclusions

We have reviewed approaches to context aware mobile language learning services, and presented the MASELTOV approach. A number of prototype contextual learning systems have been developed to date, however these have been mostly limited in scope and deployment. MASELTOV has developed a demonstrable prototype that aims to provide services to immigrant users within the challenging context of cities, and moreover to do this at scale, so that potentially the services could be used by thousands of users across major European cities. To support immigrants in a number of different areas of their everyday lives such as finding their way around, supporting social contact and language learning, all whilst they are going about their everyday lives, ten different services have been developed within the overall app. The challenge here, then, is to provide the user with what they are likely to want, when it is most useful, without overwhelming them or irritating them with constant reminders.

To provide relevant 'context-aware learning' multiple dimensions of context must be supported, underpinned by a recommendation service that can make sense of the contextual information, and respond with appropriate and timely recommendations to suitable learning resources. The MASELTOV project considers key aspects of context to be location, mode of activity, history of activity and progress, social interactions, and learners' interests. In the MASELTOV smartphone app, MApp, we derive contextual data from a number of sources. We incorporate a user profile in the registration process to gather initial user preferences, and capture dynamically generated locational data through sensors built into the user's smartphone. We have developed a context awareness service to understand what activity sensors are reporting, and record the user's activities, usage and progression in the MApp services. These data sources are passed to a user profile which is interrogated by a rule-based recommendation system and generates relevant recommendations for resources, information, and services that will support the users' learning activities.

The MASELTOV project is testing the MApp at scale in urban environments, with field trials in London, Madrid and Vienna in 2014. The first field trials are testing services in the wild for one week as a proof of technical services, with users guided through a range of semi-structured tasks. The second field trials will last over two months to test the services adoption and appropriation and understand what incidental learning and unexpected usage might take place.

By using sensor-based detection of location linked to open geographical data systems we believe our system overcomes the scalability challenge of marker-based location systems. By utilising a wide range of contextual data derived both from a user's activities and their environment, we believe we offer highly relevant recommendations for learning and can take advantage of the city as a resource for supporting contextually-aware learning.

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