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Intelligent Web Services Meet Social Computing

Web Resources Recommendation Based on Dynamic Prediction of User Consumption on the Social Web

Luis Antonio Rojas-Potosi, Luis Javier Suarez-Meza, Leandro Ordoez-Ante and **Juan Carlos Corrales**
Grupo de Ingeniea Telemtica (GIT)
Universidad del Cauca, Colombia
{*luisrojas,ljsuarez,leandro,jcorral*}*@unicauca.edu.co*

Abstract

The Web is a giant repository of resources (Service and content), where Discovery and Recommendation systems are used to deliver the best ranked list of relevant web resources that meet user requirements. Nowadays, these systems are based on the simulation and automation of the user search criteria, considering the relation between consumption trends and the different kinds of users' relationships with their virtual and physical environment, based on the information from the Social Web and mobile device sensors among others. These systems are executed once an explicit query of the user has been received; however, there are resources that are useful in specific situations, where these resources have high probability to be consumed, but, due to absence of a query they are not recommended to the users. In this regard, the question is: how to make a successful Web Resource Recommendation without the user query? In order to answer the question, this research proposal presents a novel approach to Recommend Web Resources based on Dynamic Prediction of User Consumption on the Social Web, which emulates the user behavior, the resource dynamism and the context opportunities, in real time, catching the best situations to make an asynchronous (unexpected by the user) recommendation of a useful Resources; and boost Web Resources consumption.

Introduction

Currently, Service Discovery systems and Recommendation Systems use new information sources like social apps and mobile device sensors among other, that allow develop a dimensional analysis of user consumption of web resources, considering the relation between consumption trends and the different kinds of user's relationships, with his virtual and physical environment (Pan, Aharony, and Pentland 2011). By other hand, the resources have been seen as static entities that just can be consumed and described; However, (Maamar et al. 2011) shows the social face of them, highlighting three types of social interaction: Collaboration, Substitution and Competition, between services. That approach makes us think in a dynamic concept of services that interact with another services, users and contexts.

Service Discovery is an important phase in Service Composition, and there are some approximations of his application considering Social features (Maaradji et al. 2010) and Context constraints (Suarez Meza et al. 2011), that can be applied in Recommendation Systems, and be used to infer context opportunities for Service Consumption. However these systems work once an explicit query of the user has been received; nevertheless this query sometimes never arrives, affecting some services that will not be consumed, even if they would have been useful in several of these situations. For that reason in this research proposal we present a general architecture to predict user relevant queries to support the Recommendation of Resources, arranged in the proposed architecture. The main idea is use components that emulate the behavior of the user, the service and the context in real time, catching the best situations to make an asynchronous recommendation of a specific service. The most important differentiating factors of this problem are: the asynchronous mode of the recommendation, where the system suggest resources to the user without a previous sent query; and the direct realimentation from the user opinion, caught from the successful recommendations made.

The paper is organized as follows: we first present a review of related literature to our proposal. Then, we describe the recommendation model used to lead the proposed architecture, exposed later. Finally, we conclude with the contributions of this work.

State of the art

One of the most related works is (Pan, Aharony, and Pentland 2011), the focus of it is investigation is the user installation process, and the effect of the Neighbor installation behavior over her choices. they have developed a simple discriminative model which combines individual variance, multiple networks and exogenous factors, using an mathematical optimization process for tuning it. In (Pan, Aharony, and Pentland 2011) they are focused on the Apps installation phenomena, and do not work about consumption process and the incidence of recommendation process on it; however, their model can be considered to be used on the analyzer and relation manager modules presented in this work; another of this contributions is the capture method used on their work (Aharony et al. 2011), that guide the context catcher functionality on the present work.

Regarding the resource recommendation, the approach exposed in (Ben Mokhtar and Capra 2009) propose the integration of ubiquitous information with social information of the user, using a FOAF based ontology in order to support the semantic specification and reasoning on user social preferences and tasks. On a similar direction, the work presented on (Woerndl and Schulze 2011) was focused on relevant user locations for personal information management and recognizing user activities. The above proposals addresses the resource recommendation based on the user query, however the situation-aware approach contained in them, mixed with the social services relations exposed on (Maamar et al. 2011), inspired: i) the assumption of context consumption and ii) the concept of user discovery, a task that allows to the resources found their potential clients, iii) the approach to a Simulated Environment that emulates the User, Resource and context preferences and trends, to generated unexpected and successful resource recommendations.

Recommendation Model

In order to organize the different elements that are involved in the recommendation process, this paper proposes a model, which is build from three views: i) The recommendation scenario: this corresponds to a general view of the resources' recommendation problem, who contains the hypotheses that guide the model proposed. ii) The recommendation environment, is necessary to defining the boundaries between the real world and the world simulated by the system. And iii) The Relation's Model, it allows the generalization of explicit information from the real world of the user, enabling its analysis, storage and use to support the successful recommendation to prediction.

Recommendation scenario

To present the recommendation type addressed in this paper, we will describe the recommendation scenario. The scenario consists of the following elements: i) the resource, defined as that content or service that the user can consume, nowadays, it's possible to find huge amounts of web resources such as raw data, Linked Data, Mashups, Web Services, Widgets, APIs and so on, which have been steadily increasing in recent years as the ProgrammableWeb directory evidences (Sari 2011); ii) the user, which consume the available resources, he/she usually has attached a profile where are related static and dynamic data, related with her/his personal information, situation(Woerndl and Schulze 2011), consumption history among others; iii) the context is the element that represents the state of the user in her/his physical and virtual world.

The elements behavior in the proposed scenario, follows the next assumptions:

- *The user consumes contexts and resources*: by (Dey 2001) "*Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application.*" . In this paper, the consumption is the studied interaction between a user and a resource, where the customer is the relevant entity and her/his context represents her/his environment's state any time, especially when a resource is consumed. Thus, a normal user's day can be modeled as a sequence of contexts, analogous to a services sequence, where the context can be seen as service. The above assumption allows apply the theory of Service Discovery and Service Composition of SOA in the problem presented (Suarez Meza et al. 2011). The problem, then, appears as one interesting challenge, due to emergence of an enormous amount of needed contexts to model the daily life of a person.
- *Situation:* situation is the combination of above elements (resource, user and context). There are two types of situation: the Full Situation, which represents the resource's consumption and corresponds to the tuple composed by the consumed resource, its client and its context; and the Partial Situation, which defines the set of the most situations that may occur in the daily life of a person, relating the user with her/his context. In this way, we are looking for detecting potential full situations from the partial ones in order to recommend resources on them and create new full situations
- *Resource Recommendation depends on the Context Opportunity*: the context opportunity represents the favorable combination of circumstances as context transitions (usual or unusual), arrival in contexts with high consumption rates, offer an appropriate resource for a given context, and critical changes of contextual variables, among others. In conclusion, since the type of recommendation used lacks an explicit query from the user, the closest approximation to it corresponds to the Context Opportunity.
- *Resources can look for its clients:* this is a capacity analogous to Service Discovery, but in this case the system infer and simulates the service provider criterion for its automation in the searching for potential clients among all the users.

Recommendation Environment

Currently, Service Discovery systems and Recommendation Systems use new information sources like social apps and mobile device sensors among other, that allow develop a dimensional analysis of user consumption of web resources, considering the relation between consumption trends and the different kinds of user's relationships, with his virtual and physical environment (Pan, Aharony, and Pentland 2011). The development of this kinds of environments is strongly related with the advances in Virtualization and Ubiquity, respectively, this concepts have been considered opposite, however, despite their differences, they provide useful and complementary information to abstract the Real environment of the recommendation (a combination of physical, virtual and Cognitive worlds) and modeling a Simulated Environment, which allows to emulate the system elements behavior.

Real Environment Corresponds to the sum of the information of the physical, virtual and cognitive worlds.

The information of the physical environment corresponds to that which the user can perceives by her/his senses, what is happening at any given time in physical reality, especially the state of contextual variables such as temperature, time, geolocation, walking pace, intensity light, sound intensity, orientation, communication and physical closeness with others, which can be perceived by her/his mobile device, i.e. the context variables analyzed on (Woerndl and Schulze 2011) and (Aharony et al. 2011).

Instead the Virtual World Information corresponds to what happens in the user's virtual worlds, and on-line social networks, especially the user's relationship with resources and other users (communication via messages, calls, etc).

The last Real World is the Cognitive World, defined from the Cognitive Context (Jung, Lee, and Choi 2009). Cognitive context includes preferences, mental states, tasks and social affinities of human users. This World can describe inferred states of the user, and depends on the analysis of physic and virtual worlds.

For understanding the history of user behavior in this world, we need a simple model, a tool that this world uses to storage the daily routine of the user. That model could be used for detecting changes in the user activities, or similarity with the activities made by another user.

For this model, we adopt the Finite State Machines mathematical formalism, in order to represent the user behavior. An FSM is a five-tuple (Hopcroft, Motwani, and Ullman 2006)

$$(Q, \Sigma, \Delta, \sigma, q_o) \tag{1}$$

Where

Q is a finite non-empty set of states, where each state corresponds to a different context.;

Σ, is a finite non-empty set of input, such inputs are triggered like events during the used time for each task performed.

Δ, set of symbols denoting the possible outputs, In this case each state transition can output the value of the recommendation pertinence, or a recommendation as such. there may be a null output. Nonzero outputs in the real world denote the consumption of a resource, in the Simulated Environment the recommendation of a potential resource.

σ, transition function mapping $Q \times \Sigma$ to $Q \times \Delta$, this function in the real world defines the sequence of contexts, in the virtual environment, this function is the result of a probabilistic analysis of the possible following context.

$q_o \in Q$, initial state, initial context.

The previous model represents the user behavior in a simple manner, capturing the changing consumption of contexts and resources. The interaction between user, contexts and resources is stored using a Relations model, presented below.

Simulated Environment It corresponds to a parallel world in which the three elements of the recommendation scenario: User, Context and Resources, are represented by an avatar, each one, which is fed with real-world information to try to emulate it in a logical level in real time. To build this emulators we can use BDI (Beliefs, Desires and Intentions) Multi-agents, to simulate the elements interaction and create relations and groups automatically, by associations made by action/reaction interactions.

The two main purpose of the Simulated World are: i) emulating the habitual user behavior in real time to discover anomalies associated with contextual opportunities, even simulate a general anomalous behavior from the analysis of context related users; ii) can emulate a possible reaction to another element action, based on his historical behavior trends and preferences, through this way new relations can be made, and useful resources founded. The last purpose allows simulate a world where the resources can look for their potential costumers, and the users can receive resources recommendations in accordance of a simulation of their reaction, which is predicted by the information from their Real World.from his Real World Information.

To achieves the second purpose the simulated World uses the Action/Reaction model, which allows simulate the interaction between elements. The main concept of this model is the Collision, referred to the exchange of information through requests and responses between two elements or groups of elements in the system, resulting in the establishment of relationships or discard them. The collition is a process where the elements have a negociation of their relationship type and weight. The collision will take place until one of parties stops it, or the negotiation of relationship has ended.

This type of model allows the automatic organization of groups of elements, the users search for services and the relationship between users with similar preferences but no social link, among others.

Relations Model

The relations model is used to optimize system performance, because it supports the development of indexing techniques used to segment users, resources and contexts, allowing the reduction of search space of queries like: what are the most appropriate services for this situation?, what are the situations suitable for a specific service? and what users are more likely to consumur a service?.

The basic interactions considered in the model are: *i) User-User* (i.e. Call Log, Blue-tooth Proximity, Friendship, Affiliation (Pan, Aharony, and Pentland 2011)), *ii) User-Context* (i.e. Consume and Frequency), *iii)User-Resource* (i.e. Consume, Successfully recommendation, Unsuccessfully recommendation), *iv) Context-Context* (i.e. Similarity, Next), *v) Context-Resource* (i.e. Consume, Successfully recommendation, Unsuccessfully recommendation), *vi) Resource-Resource* (i.e. Collaboration, Substitution, Competition (Maamar et al. 2011)).

The Relations Model is abstracted from the information contained in real and simulated environments. There are two types of relationships: relations of low-level, which are the relationships that exist directly between a pair of atomic elements, and high-level relationships, those relationships in which one of the two elements conforming, is a group of elements, as presented by the Fig 1.

Low level Relations (LLR) They exist between atomic elements of the Recommendation Scenario, from them can be

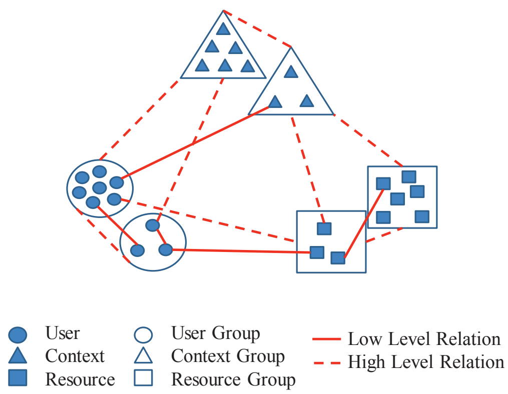

Figure 1: *Relations between elements*

generalized and reach high-level relations. The significance of these types of relationships depends on the type of interaction itself. i.e. for the type User-User may have relationships that represent friendship, or similarity of profiles. Graphs are used for its representation, as in (Pan, Aharony, and Pentland 2011).

High level Relations (HLR) For understanding of this type of relationships, it is necessary to speak about groups of elements resulting from the application of indexing systems that act on the information stored in the model of real and simulated environment. This groups of elements allows characterize similar stereotypes of behavior, goals and needs of the different system elements.

WoBe: Recommendation Architecture

In this section we present an overview of the proposed architecture for the Web resources recommendation based on dynamic prediction of resources consumption, this architecture is called Wobe (Would Be), is presented in the Figure 2 and has the following components:

Context Catcher: this module makes possible the first step in the recommendation process: to extract context variables that lead to a situational Understanding (Shih, Narayanan, and Kuhn 2011). The pervasiveness of mobile phones has made them ubiquitous social sensors of location, proximity and communications(Aharony et al. 2011); and this module use them to capture contextual variables, that are typically derived from various information sources such as sensors, audio, location, time, application content and user-device interactions, among others, by using a broad range of Techniques Such as signal processing, machine learning, natural language processing, and so on. Also, on this way this module can modeling the user's current situation.

User Behavior Monitor: it detects the changes of situation of the user, and complete the user behavior model, based on FSM. Moreover, it queries the system to keep updated options to complete partial caught situations. Two of its main tasks are i) the detection of unusual behavior, by matching the User Behavior Emulator state with the current User Situation; and ii) the evaluation of the pertinence of resource recommendation, to determine its recommendation level and ranking.

Recommender: this module is which delivery the recommended resources to the user, the recommendation delivery involves manage levels of recommendation based on the Cognitive context, and the evaluation of the pertinence of recommendation.

Re-configurator: This is the module responsible of the direct feedback from the user decision criteria (i.e. the acceptance or rejection of a recommendation).

User Behavior Profile: this profile is a generalization of the habitual user behavior represented by FSM.

User Behavior Emulate: this entity emulates the general user behavior stored in the User Behavior Profile, in real time, to enable the unusual user behavior detection, by matching the state of this entity with the current User Situation.

User Behavior Learner: its principal duty is the single user information analysis and generalization. It has as information sources: feedback from the re-configurator module, the user action/reaction emulator and the User Behavior Emulator; and new information from the Context Catcher, this information is stored, consulted, related and indexed using the Relation and Index Manager Modules. After learning from the above sources information it has as outputs: i) the definition of the User Behavior Profile, ii) the definition of the User Action/Reaction profile. The main task on its analysis is find triggering situations for the FSM transition functions characterization, different from that used by default: the time.

User Action/Reaction Profile: it contains the user preferences for the possible requests/responses to an eventual interaction with another elements of the system, like other users, resources and contexts. This profile is inferred from history of situations of the user and his/her recommendation history (a history of the acceptance or rejection of recommendations).

User Action/Reaction Emulator: this entity emulates the Action/Reaction behavior of the user in a collision with another entity, based on the User Action/Reaction Profile.

Query Manager: this element has three main goals: i) responding to requests from the User Behavior Monitor and Element Profile Collision emulator with a ranking of elements based on the weighted mix of real and emulated criteria; ii) Storage and analyze the query history, detecting general trends of element segments, in real time, based on the set of current queries, this information is used to the eventual detection of general needs (situations) and the recommendation of its related resources, iii) Query to the user, through this component we can suggest the resources that were recommended by the Simulated Environment criterion, and depending on the response of the user, tuning the simulated environment or modify the resources consumption in the Real Environment. Based on the information analyzed by this module, the system would mix the different responses to the queries and generate new composed resources.

Element Discover: it recovers ordered lists of elements using the information provided by the Relation and Index

Manager modules.

Relationship Manager: in the Recommend Environment Scenario the data enable us to construct multiple network modalities of the community such as the phone communication network, physical face-to-face encounters network, on-line social network, self-reported network, and more(Aharony et al. 2011). Furthermore as most real–world networks are inherently complex dynamical systems, where both attributes of the nodes and topology of the network can change with time(Cho, Steeg, and Galstyan 2011). therefore it is necessary a module dedicated to measure and infer the changes and the influence between elements (Altshuler, Pan, and Pentland 2011); and manage the life cycle of relationships and relationships modalities in the recommendation environment (creation, enrichment and destruction). This module can use ontologies (i.e. FOAF based Ontologies as presented in (Woerndl and Schulze 2011)) to recommend additional items that are not explicitly related to the user. As a result of above functionalities, this module allows consult: specific relationships of high or low level and graphs of relationship networks, considering the influence between elements and the change of their relationships.

Virtual Relation Catcher: is a collector of the Virtual Environment of the user.

Index Manager: A key challenge of data-driven social science is the gathering of high quality multi-dimensional datasets (Aharony et al. 2011), and their organization, because most of the techniques of diffusion optimization, used by modules, like the Relation Manager, are conditioned to the influence space (number of elements of the influence study), therefore this module is an index system aimed to segmenting the elements and optimize the inference space. This component manage the life cycle of the groups of elements and their kinds; the group life cycle is: creation, expansion, contraction, splitting(Baltrunas and Ricci 2009), joining and destruction. The Index Manager provides group information like its members, dimensions, kinds (subsection of a dimension) among other information related with the element's indexing process. The Index Manager is responsible of limit the search space of queries made by the Element Discover and the analysis processes made by the Analyzer.

Analyzer: it is the brain of the Real Environment, its main goal is the constant optimization of the Relation and Index Managers; i. e. in (Pan, Aharony, and Pentland 2011) is described a model to infer an optimal composite network, the network that best describes the App installation, to do this they need to train their system and found optimal values for its parameters, when they reach those values, their model can predict the App Installation. In WoBe the tunning or the model parameters is made by the analyzer, and its application is made by the Relation Manager. This module just consider real and explicit information about the Real World, and its deal is optimizing all the abstraction processes that infer implicit information (relations and groups).

Action/Reaction Profiles: this a common layer for Resources, Contexts, Users groups, Resources Groups, Contexts Groups. This profile contains the elements preferences for the possible requests/responses to an eventual interaction with another elements of the system. In the groups this

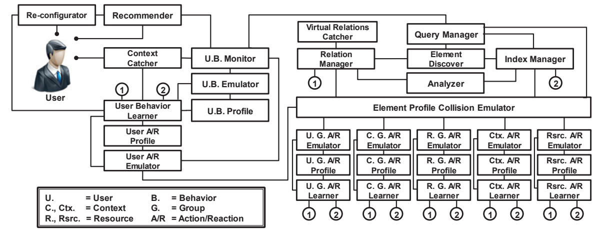

Figure 2: *WoBe: General Architecture*

profile contains the general trends of their members. These profiles are inferred from the relations history.

Action/Reaction Learners: its principal duty is the element and elements groups information analysis and generalization, its main information sources are the Action/Reaction Emulators, the Relation and Index Manager Modules; with that information this module generate and tune an Action/Reaction Profile. This module is responsible of writing new Simulated relationships, this relationships can be used by the Collision Emulator.

Action/Reaction Emulators: this entity emulates the Action/Reaction behavior of the elements and elements groups in a collision with another entity, based on their Action/Reaction Profile. The new relationships formed by the collision are sent to the Action/Reaction Learner to be stored.

Element Profile Collision Emulator: nodes tend to interact with similar nodes, whereas the latter asserts that the evolution of a node's attributes are affected by its neighbors(Cho, Steeg, and Galstyan 2011), this process can be analyzed by a probabilistic way (i.e. The relation Manager), but that way could be slow to adapt new elements, like new contexts, users and resources, because the evolution on the relation model and groups depends on their real interaction with another elements. Therefore, in this paper we propose a Simulated Environment, in which those interactions are simulated by a Action/Reaction model. The formed simulated relationships affect the ranking of recommended elements, delivered by the Query Manager, which include a kind of noise to the recommendation, by the delivery of resources related by simulation. The Simulated Environment can influence the Real Environment just when the user consumes a recommended resource by simulation, information used for tunning the Collision Emulator. The collision emulator is referee that manage the collision spread between elements emulators, to do so, it uses the information of real explicit, real implicit and and simulated Relations, and the groups information, that information is provided by the Index and Relation Manager Modules. This module allows the automatic indexation of elements, by the simulation of a members discovery process, using a hierarchical search of elements

Conclusion and Open Issues

In this paper, we have proposed a new approach to overcome the problem of the resource recommendation without an explicit query from the user. To do so we propose a Real Environment analysis founded on works related with information diffusion models, capable of predicting future trends based on the analysis of past social interactions between the community's members. Those works probed that social factors have an effect on the physical activity behavior, motivation, and adherence over time. To use that kind of analysis was necessary consider a collection phase of information from real and virtual worlds and modules dedicated to learning from the resource consumption behavior, leading to the creation of implicit relationships, from explicit and real ones.

To adapt those models to the Resource Recommendation without an explicit query was necessary insert a monitor system, for detecting the change of situation of the user, and identify context opportunities to do successful recommendations. However the system presents a high challenge related to the manage of high amount of information, specially the huge amount of contexts.

To conclude, one of the main ideas presented in this paper is the emulation of the elements of the Recommend Scenario, to achieve three important issues: i) The automatic indexation of elements ii) the automatic segmentation of users for resources iii) the recommendation of new elements not perceived by the learners of the system. Even with the benefits of the proposed approach, there are still some challenging issues to be addressed as future work: the analysis of privacy requirements of the user profile and the asynchronous composition of new resources based on situation analysis.

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References

Aharony, N.; Pan, W.; Ip, C.; Khayal, I.; and Pentland, A. 2011. The social fmri: measuring, understanding, and designing social mechanisms in the real world. In *Proceedings of the 13th international conference on Ubiquitous computing*, UbiComp '11, 445–454. New York, NY, USA: ACM.

Altshuler, Y.; Pan, W.; and Pentland, A. 2011. Trends prediction using social diffusion models. *CoRR* abs/1111.4650.

Baltrunas, L., and Ricci, F. 2009. Context-based splitting of item ratings in collaborative filtering. In *Proceedings of the third ACM conference on Recommender systems*, RecSys '09, 245–248. New York, NY, USA: ACM.

Ben Mokhtar, S., and Capra, L. 2009. From pervasive to social computing: algorithms and deployments. In *Proceedings of the 2009 international conference on Pervasive services*, ICPS '09, 169–178. New York, NY, USA: ACM.

Cho, Y.-S.; Steeg, G. V.; and Galstyan, A. 2011. Co-evolution of selection and influence in social networks. In Burgard, W., and Roth, D., eds., *AAAI*. AAAI Press.

Dey, A. K. 2001. Understanding and using context. *Personal Ubiquitous Comput.* 5:4–7.

Hopcroft, J. E.; Motwani, R.; and Ullman, J. D. 2006. *Introduction to Automata Theory, Languages, and Computation (3rd Edition)*. Boston, MA, USA: Addison-Wesley Longman Publishing Co., Inc.

Jung, J. J.; Lee, H.; and Choi, K. S. 2009. Contextualized recommendation based on reality mining from mobile subscribers. *Cybern. Syst.* 40:160–175.

Maamar, Z.; Faci, N.; Badr, Y.; Wives, L. K.; dos Santos, P. B.; Benslimane, D.; and de Oliveira, J. P. M. 2011. Towards a framework for weaving social networks principles into web services discovery. In *Proceedings of the International Conference on Web Intelligence, Mining and Semantics*, WIMS '11, 51:1–51:11. New York, NY, USA: ACM.

Maaradji, A.; Hacid, H.; Daigremont, J.; and Crespi, N. 2010. Towards a social network based approach for services composition. In *Proc. IEEE Int Communications (ICC) Conf*, 1–5.

Pan, W.; Aharony, N.; and Pentland, A. 2011. Composite social network for predicting mobile apps installation. In Burgard, W., and Roth, D., eds., *Twenty-Fifth AAAI Conference on Artificial Intelligence*. AAAI Press.

Sari, S. W. 2011. Diversity of the mashup ecosystem. In *International Conference on Web Information Systems (WEBIST)*.

Shih, F.; Narayanan, V.; and Kuhn, L. 2011. Enabling semantic understanding of situations from contextual data in a privacy-sensitive manner. In *Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence*.

Suarez Meza, L. J.; Rojas-Potosi, L. A.; Corrales, J. C.; and Steller, L. 2011. Service discovery in ubiquitous computing environments. In *The Sixth International Conference on Internet and Web Applications and Services, ICIW 2011*, 978-1-61208-124-3, 1–9. St. Maarten, The Netherlands Antilles: IARIA.

Woerndl, W., and Schulze, F. 2011. Capturing, analyzing and utilizing context-based information about user activities on smartphones. In *AAAI Publications, Workshops at the Twenty-Fifth AAAI Conference on Artificial Intelligence*.